Reflectance Retrieval for Hyperspectral Imagery Collected Over Urban Environments

A Thesis Presented
by

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I dedicate this thesis to my parents Judy and Evan who have always provided me with their unwavering support.
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<td>ASR</td>
<td>Automated Solar Radiometer. Radiometer used to measure direct and indirect solar illumination over a certain time period by automatically tracking the sun.</td>
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<tr>
<td>COMPASS</td>
<td>COMPact Airborne Spectral Sensor. An experimental hyperspectral sensor developed in the early 2000s.</td>
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<tr>
<td>BRDF</td>
<td>Bidirectional Reflectance Distribution Function. The function that governs the fraction of radiation reflected by a material from given angles of incidence and observation.</td>
</tr>
<tr>
<td>CAD</td>
<td>Computer-Aided Design.</td>
</tr>
<tr>
<td>FOV</td>
<td>Field of View. The angular viewing extent of a sensor.</td>
</tr>
<tr>
<td>IMUGPS</td>
<td>Inertial Measurement Unit / Global Positioning System. Sensor suite that records the platform’s roll, pitch, yaw, latitude, longitude, and altitude.</td>
</tr>
<tr>
<td>LADAR</td>
<td>LAser Detection And Ranging. Remote sensing method that creates high-resolution 3D point clouds.</td>
</tr>
<tr>
<td>LTE</td>
<td>Light Transport Equation. The governing energy balance equation for surface reflections.</td>
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<tr>
<td>LWIR</td>
<td>Long-Wave InfraRed. The portion of the electromagnetic spectrum that extends between 5000nm and 14000nm. Materials are emissive in this region.</td>
</tr>
<tr>
<td>MODTRAN</td>
<td>MODe rate resolution atmospheric TRANsmission®. Atmospheric compensation program used for reflectance retrieval.</td>
</tr>
<tr>
<td>MWIR</td>
<td>Mid-Wave InfraRed. The portion of the electromagnetic spectrum that extends between 3000nm and 5000nm. Materials are emissive in this region.</td>
</tr>
<tr>
<td>NIR</td>
<td>Near-InfraRed The portion of the electromagnetic spectrum that extends between 750nm and 1100nm. Materials are reflective in this region.</td>
</tr>
<tr>
<td>PSF</td>
<td>Point Spread Function The response of a system (in our case the atmosphere or a sensor) to a single point of light.</td>
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RIT  Rochester Institute of Technology. Researchers here performed initial research into exploitation algorithms for hyperspectral imaging over urban environments.

SNR  Signal to Noise Ratio The ratio of signal to noise present in a measured signal.

SAM  Spectral Angle Map. Similarity metric that calculates the angle between two spectral vectors.

SHARE  SpecTIR Hyperspectral Airborne Rochester Experiments. HSI and LADAR co-collection campaigns conducted at RIT to support hyperspectral data exploitation in urban environments.

SWIR  Short-Wave InfraRed. The portion of the electromagnetic spectrum that extends between 1100nm and 3000nm. Materials are reflective in this region.

VNIR  Visible Near InfraRed. The portion of the electromagnetic spectrum that extends between 400nm and 1100nm. Materials are reflective in this region.
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Abstract of the Thesis

Reflectance Retrieval for Hyperspectral Imagery Collected Over Urban Environments

by

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Hyperspectral Imaging (HSI) aims to classify targets based upon the extracted spectral reflectance signatures of objects within an image. This reflectance retrieval process estimates and compensates for the atmospheric effects on measured radiance data. Traditional reflectance retrieval methods rely upon simplifying assumptions about the target scene geometry. In particular, these methods require the target to exist in an open environment, in which all scene-incident solar and atmospheric illumination reach the target. When the open environment assumption is invalid, such as in urban environments where targets exist in complex lighting conditions, traditional reflectance retrieval methods will fail.

This thesis builds upon recent research into reflectance retrieval methods that do not rely on the open-environment assumption. These approaches fuse hyperspectral imagery with a model of target scene geometry to estimate the irradiance incident to targets in urban settings. In this thesis, we discuss an improvement to this method that fully models how light propagates through an environment before it reaches the target. In theory, this new irradiance estimate will fully account for the complex illumination conditions found in urban environments, thereby enabling accurate reflectance retrieval for targets in these settings. This model can be adapted to solve the forward problem of radiance estimation or the inverse problem of reflectance retrieval.

In this thesis, we discuss this new framework for estimating light propagation through urban scenes. Our main contribution to the problem of urban reflectance retrieval is the performance analysis of this method. For our analysis, we use this method to estimate the radiance that was measured by an HSI sensor during a collection campaign over two representative urban scenes. We then evaluate the areas in which this model performs well and those in which the model is unable to estimate this measured radiance. We trace some errors to simplifying assumptions made by the
model and identify multiple possible sources of error for other observed modeling discrepancies. In all cases, we recommend modeling improvements to address these errors and experiments to test our presented hypotheses. Finally, we use this model to retrieve the reflectance signatures of the targets in our urban scenes. In doing so, we show that this model greatly improves the accuracy of retrieved reflectance over that retrieved by traditional models for targets in complex illumination conditions.
Chapter 1

Introduction

In this chapter, we give a high-level overview of Hyperspectral Imaging (HSI) and introduce the problem of reflectance retrieval in urban environments. Reflectance retrieval is a required step for HSI data exploitation. We introduce traditional approaches to this problem and discuss how their simplifying assumptions cause them to fail in urban settings. In the early 2010s, Rochester Institute of Technology (RIT) developed initial solutions to this challenging problem. We detail their solution to this problem and its potential inaccuracies. This leads to our discussion of the contributions made by this thesis to the problem of urban reflectance retrieval. Lastly, we provide an overview of each chapter in this thesis.

1.1 Introduction to Hyperspectral Imaging

HSI is a remote sensing technique that measures electromagnetic radiation over hundreds of contiguous wavelength bands. Standard cameras measure incident radiance over three spectral bands: red, green, and blue. While the resulting color image has a higher spatial resolution than the corresponding hyperspectral image, material classification and target detection is extremely difficult when relying on spatial features alone. Because every material has a unique spectral signature, the high spectral resolution is used for material classification and target detection. Hyperspectral sensors are typically mounted on airborne and spaceborne platforms. As the platform travels, the sensor constantly scans the ground beneath it. Successive scans are compiled into a hyperspectral data cube. Figure 1.1 shows this process. The first two dimensions \((x, y)\) of the cube are the spatial dimensions that represents the total scan area. The third dimension \(z\) is the spectral dimension and contains the spectral response of the given pixel at every wavelength in the bands the sensor measures over.
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Figure 1.1: HSI data acquisition. As the platform travels, the HSI sensor continually scans the ground beneath it. The measured data is assembled into a hyperspectral data cube. The cube’s dimensions $(x \times y \times z)$ correspond to the two spatial dimensions and one spectral dimension, respectively.

HSI sensors operate in four spectral regions: the Visible Near InfraRed (VNIR) and Short-Wave InfraRed (SWIR) wavelengths, defined respectively as $400 \text{–} 1100\text{nm}$ and $1100 \text{–} 3000\text{nm}$ or the Mid-Wave InfraRed (MWIR) and Long-Wave InfraRed (LWIR) wavelengths, defined as $3000 \text{–} 5000\text{nm}$ and $5000 \text{–} 14000\text{nm}$ respectively. The measured portion of the electromagnetic spectrum, and thus the sensor used, is application specific. In the VNIR, SWIR regions, solar illumination dominates and the measured radiation has been reflected off of the ground targets. Here, targets are classified by their reflectance spectra. In the MWIR, LWIR regions, material emission dominates; measured radiation has been emitted from the targets. Here, targets are classified by their emissivity and temperature. The VNIR, SWIR wavelengths have been successfully used to detect solid targets while the MWIR, LWIR are generally used to detect gasses [3]. In this thesis, we will work exclusively in the VNIR, SWIR.

For example, many types of vegetation are visually similar, and artificial materials, such as camouflage netting, are designed to visually blend in with their surroundings. HSI sensors have lower spatial resolution than RGB cameras, but their increased spectral resolution is a powerful tool for material classification and target detection [3]. Grass is spectrally distinguishable from trees,
CHAPTER 1. INTRODUCTION

Figure 1.2: Examples of reflectance spectra for various materials: (a) granite, (b) sand, and (c) vegetation. These reflectance spectra are from the ASTER data set [1].

and both are spectrally distinguishable from artificial camouflage. Examples of various reflectance spectra of common materials are shown in Figure 1.2.

This spectral separability of materials provides a wide range of civilian and military applications for HSI. Hyperspectral surveys can segment images by material and vegetation type, detect surface features, or locate diseased crops; detect various types of paints and materials used in man-made structures; aid in search and rescue operations by segmenting natural and artificial materials in the search space; or assist military reconnaissance missions [3]. Since vegetation has a distinctive spectral change between the visible and infrared wavelengths (known as the red edge), some astronomers even hypothesize that the first signs of alien life will be found via HSI [6].

[HSI] sensors measure radiance, which is defined as the amount of radiant flux incident to or leaving a surface per unit projected area per unit solid angle. Radiance reaches the sensor after following the path illustrated in Figure 1.3, where it undergoes significant changes due to atmospheric transmission and reflection. If the target is in an urban environment, building reflection will cause additional radiance changes by shading or indirectly illuminating surfaces in the scene. As a result of these external factors, measured radiance is not dependent on a material alone. If two identical targets are measured under varying conditions, their measured radiances will not be the same. Radiance is therefore not a reliable metric for target detection and material classification.

Material reflectance is the intrinsic property used for detection and classification. Every material has a unique reflectance signature based upon that material’s chemical composition. However, reflectance cannot be measured directly. Instead, it must be estimated by taking the ratio of surface-reflected to surface-incident radiation. Estimating reflectance is difficult because, as shown in Figure 1.3, the atmosphere and the environment cause the radiance of a light ray to deviate from known values as it propagates to and from a surface. The art of processing HSI data is accurately
estimating reflectance from measured radiance. The first step of this process is data calibration, which uses a known sensor characterization to correct the distortions made during measurement. Successful data calibration will produce a measurement that is identical to the radiance incident to the sensor at the time of measurement. The second processing step is atmospheric compensation. Aerosols, vapors, and gases in the atmosphere absorb and scatter electromagnetic radiation. This scattering and absorption affects the radiance incident to the surface, as well as the radiance that is reflected by the surface and into the sensor. Aerosol content varies by time of year, time of day, and geographic location; the same surface imaged under varying atmospheric conditions will yield distinct radiance measurements. Atmospheric effects are removed by estimating reflectance from measured radiance in a process called reflectance retrieval. During atmospheric compensation, atmospheric models predict how solar radiance propagates through the atmosphere before it reaches the surface, and how radiance reflected by the surface propagates through the atmosphere before reaching the sensor. The latter calculation allows at-sensor radiance to be converted to ground-leaving radiance. If a number of simplifying assumptions are made, reflectance can then be estimated by
CHAPTER 1. INTRODUCTION

Figure 1.4: Flow chart outlining the required processing chain to convert raw hyperspectral data to an exploitable form. Flowchart derived from Chapter 1 of [3].

Taking the ratio of this ground-leaving radiance to the ground-incident radiance [3]. Successful atmospheric compensation for the aforementioned surfaces will yield identical reflectance spectra. Every material has a unique reflectance signature; identical targets will have identical reflectance signatures. With target reflectance estimated, the measured data can then be exploited by target classification algorithms. Figure 1.4 illustrates these processing steps.

HSI data exploitation operates by comparing retrieved spectral signatures to known target spectral signatures. Accurate reflectance retrieval is therefore vital for successful material classification and target detection. Due to the complexity of modeling light transport through the environment, traditional reflectance retrieval methods utilize a number of simplifying assumptions:

1. The surface is a perfectly diffuse reflector.
2. The surface is illuminated only by sunlight and scattered skylight.
3. The atmosphere is clear and free of clouds.
4. The surface exists in an open environment, away from trees or buildings.

As a result of these assumptions, traditional reflectance retrieval methods require illumination to be location-independent throughout the scene [7].

Urban environments pose a unique challenge for HSI data exploitation. Urban scenes violate the open environment assumption: buildings can cast shadows on targets to create obscured lighting conditions or reflect sunlight onto targets to create indirect lighting conditions. The resulting lighting conditions are not location-agnostic as expected by atmospheric compensation based reflectance retrieval methods. Under urban lighting conditions, these traditional methods will be inaccurate, which greatly reduces the performance of target detection algorithms. Reflectance retrieval methods for urban environments must therefore take into account local scene geometry to accurately predict true target illumination conditions.
1.2 Previous Work

The idea of applying scene geometry models and computer rendering techniques to the remote sensing problem of reflectance retrieval is not new. The Radiosity method for urban light propagation was first introduced in the 1990s by [5]. Radiosity uses a system of linear equations to estimate how light propagates throughout a scene with known geometry and spectral characteristics, taking into account the viewing relationships between surfaces. This method proved effective for modeling light propagation through foliage, since it preserves the spatial orientation of leaves during its calculations [8]. As introduced in [5] and [3], the Radiosity method is a forward model for estimating measured data. As a system of linear equations, if target-leaving radiance is known, this forward Radiosity model may be inverted to solve for the diffuse reflectance of a material. This is known as the adjoint Radiosity method and was introduced in [7]. Adjoint Radiosity provides the foundation for urban reflectance retrieval. In [7], adjoint Radiosity is demonstrated using a simplified computer-generated scene. In [9], Ewald et al demonstrate the feasibility of using adjoint Radiosity for reflectance retrieval using real-world data. They created scene geometry models from measured LADAR data, which were used with Radiosity to calculate the radiance incident to all locations in the target scene. By fusing these scene geometry models with measured spectral data, adjoint Radiosity was then used to estimate the diffuse reflectance spectra for targets in urban lighting conditions. Adjoint Radiosity provides the basis for the urban reflectance retrieval method utilized in this thesis.

Researchers at RIT conducted additional related work towards the exploitation of HSI data taken over urban environments. They performed two data collects: SpecTIR Hyperspectral Airborne Rochester Experiments (SHARE) 2010 [10] and 2012 [11]. During these data collects, HSI and LADAR data was collected over a portion of the RIT campus. The data collect studied obscured illumination targets, and in [12], RIT researchers showed that traditional reflectance retrieval methods provided highly inaccurate estimates of these targets. To address these inaccuracies, the LADAR data provided a 3D point cloud of the scene geometry, which facilitated the estimation of true target illumination conditions. The HSI data was mapped to the LADAR point cloud, such that each location in the scene geometry had an associate radiance spectrum. This fused HSI and LADAR data was used to create a method for radiance estimation in the presence of obscured illumination [13].

This work demonstrates the feasibility of radiance estimation and reflectance retrieval for urban environments. The Radiosity method allows the estimation of light propagation through urban environments while [9] and [13] have shown the potential for generating scene geometry models.
from measured \textit{LADAR} data. They also showed how measured \textit{HSI} data can be mapped to such scene geometry models. This provides the foundation for a complete performance analysis of such urban light propagation methods. Such model performance evaluation is the main contribution of this thesis.

### 1.3 Contributions of Thesis

In this thesis, we analyze a method for modeling light propagation throughout an urban environment. This method enables both radiance estimation and reflectance retrieval. The major contribution of this thesis is the full performance evaluation of this method. We then provide recommendations for future work to improve the accuracy of this method.

We will first describe this modeling framework for fully estimating light propagation throughout an urban scene. Like traditional reflectance retrieval methods, it utilizes atmospheric compensation techniques to determine the scene-incident irradiance from direct sunlight and scattered skylight. Unlike traditional methods, it removes the open-environment assumption by incorporating knowledge of scene geometry into the model, as described in [7]. This allows it to estimate the true illumination conditions at an urban target. As a light propagation model, this method can be configured to solve either the forward radiance estimation problem or the inverse problem of reflectance retrieval. In either case, it requires accurate knowledge of scene geometry and a method for registering this geometry to measured \textit{HSI} data. Measured data is required in order to evaluate this method. We will describe a data collection campaign conducted over two representative urban scenes. This campaign collected all necessary data to develop this method: \textit{VNIR}, \textit{SWIR}, \textit{HSI} radiance, atmospheric information to create atmospheric models, and scene geometry information to create scene models and populate them with the spectral properties of constituent objects.

The primary contribution of this thesis is to use the data measured during this data collection campaign to fully evaluate the performance of this urban light propagation model. To determine model performance, we configured the model to estimate the radiance measured during our data collection campaign. Accurate radiance estimates would imply accurate ground-truth measurements, atmospheric models, and above all, accurate light propagation modeling throughout our scene. We show that while this model successfully estimates our measured ground-leaving radiance, estimation of measured at-sensor radiance is more difficult. Observed at-sensor radiance modeling errors facilitate model analysis; we hypothesize that many observed errors can be attributed to several invalid assumptions.
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The final contribution of this thesis is to recommend improvements to this model that address the modeling errors we uncovered. While this model is not reliant on the open-environment assumption, it does utilize other simplifying assumptions, as outlined in detail in Chapter 5. Future work should first and foremost remove the model’s reliance on these assumptions.

1.4 Thesis Outline

The remainder of this thesis is organized as follows:

Chapter 2

In Chapter 2 we provide the conceptual background for reflectance retrieval. We first define the fundamental radiometric quantities of reflectance, irradiance, and radiance, as well as the mathematical background for radiative transfer. Traditional atmospheric compensation-based reflectance retrieval methods are described, as well as how the simplifying assumptions they make cause them to fail in urban environments. We then introduce our method for reflectance retrieval in urban settings.

Chapter 3

In Chapter 3 we discuss in detail the data collection campaign which collected all necessary data to validate the method for urban reflectance retrieval. This data includes airborne HSI and LADAR and panchromatic imagery, as well as ground-based atmospheric and ground-truth radiance and reflectance factor measurements for each of our targets. We describe the urban scenes over which data was collected.

Chapter 4

Having introduced the collected data, in Chapter 4 we describe the specifics of this urban light propagation model implementation. First, we detail the method for generating scene geometry models and the technique for co-registering these models to measured HSI data. Special cases of radiative transfer for 3-dimensional scenes are then derived. We then describe the MATLAB®-based model for using these equations, scene geometry, and measured data to estimate radiance and retrieve reflectance. Finally, we validate this rendering technique by comparing its rendered radiance to that of a secondarily implemented rendering method.
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Chapter 5

Chapter 5 fully analyzes the performance of this model by solving the forward problem of radiance estimation. First, to better understand the mechanics of indirect and obscured illumination, we examine the contributing sources of irradiance for obscured and indirect illumination targets. Next, we compare our estimated and measured ground-leaving radiance. This provides a baseline for the following comparison between our estimated and measured at-sensor radiance. Hypothesized sources of radiance modeling error are presented we recommend modeling improvements to address these errors.

Chapter 6

Chapter 6 concludes this thesis. It is split into two sections. First, we summarize the contributions of this thesis towards the urban reflectance retrieval problem. The main such contribution is the in-depth analysis of our modeling performance and the suggestion of experiments which should be conducted to determine the source of observed modeling errors. The second section describes in detail our suggested next steps for developing this model.
Chapter 2

Background

HSI sensors measure the spectral radiance that is reflected or emitted by the target scene with the goal of material classification and target detection. Target detection and classification algorithms operate by comparing measured spectra with that of a spectral library \[14\]. However, measured radiance is an ineffective metric for target detection algorithms because it depends on environmental factors external to the target, such as local illumination and atmospheric conditions. The atmosphere and environment can have drastic effects on solar irradiance as it travels from space to the target and once again from the target to the sensor. Reflectance is instead the radiometric quantity of choice for detection and classification because it is an intrinsic material property. Reflectance retrieval is inherently a light propagation problem: accurate reflectance can only be retrieved if the effects on light as it propagates throughout the atmosphere and environment are accurately modeled.

To motivate this process, we first introduce the fundamental radiometric quantities in Section 2.1. Then in Section 2.2, we introduce the radiative transfer equation and the absorption, scattering, and emission processes that it models. In Section 2.3, we next discuss how radiative transfer is used for reflectance retrieval and the simplifying assumptions that traditional reflectance retrieval methods make to account for incomplete scene information. To illustrate the importance of accurate reflectance retrieval, in Section 2.4, we introduce metrics for target detection using HSI data. When the assumptions made during reflectance retrieval are invalid, retrieved reflectance will be inaccurate and the performance of detection algorithms based upon these metrics will decrease. This is the case for urban environments, when the open-environment assumption is violated. In Section 2.5, we discuss how urban environments cause traditional reflectance retrieval methods to fail and we present our solution for reflectance retrieval in these settings. Finally, Section 2.6 summarizes this chapter.
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2.1 Fundamental Radiometric Quantities

In this section, we define the fundamental quantities of reflectance, irradiance, and radiance. This provides the basis for future discussion of reflectance retrieval. A material’s reflectance defines the amount of radiant flux that it reflects as a function of incident radiant flux and given angles of incidence and reflection, where radiant flux $\Phi$ is the rate at which energy flows through an area per unit time. Reflectance $\rho$ is then defined as the ratio of reflected to incident radiant flux [3]:

$$
\rho(\omega_r, \omega_i; \lambda) = \frac{d\Phi_r(\lambda)}{d\Phi_i(\lambda)} \quad (2.1)
$$

where $\omega_r$ is the direction in which the radiant flux is reflected by the material, $\omega_i$ is the direction in which the incident radiant flux is incident to the material, and $\lambda$ is wavelength.

Reflectance retrieval is the process in which incident and reflected radiant flux are estimated from solar irradiance and measured radiance. Irradiance $E$ is the total flux per unit area. For a receiving area $dA$ at a location $x$, it is defined as [3]:

$$
E(x, \lambda) = \frac{d\Phi(x, \lambda)}{dA} \quad (2.2)
$$

and has units $[W/cm^2 \cdot \mu m]$. Radiance $L$ is defined as flux per unit projected area per unit solid angle received or emitted by any surface. For an angle $\theta$ between the surface normal and incident radiant flux, the differential projected area is defined as $dA_{proj} = dA \cos \theta$. Radiance at a surface $x$ can then be expressed as [3]:

$$
L(\omega; x, \lambda) = \frac{d^2\Phi(\omega; x, \lambda)}{dA \ d\omega \cos \theta} \quad (2.3)
$$

and has units $[W/sr \cdot cm^2 \cdot \mu m]$.

2.2 Radiative Transfer

The radiative transfer equation is a volumetric equilibrium equation that models the effects of volumetric scattering, absorption, and emission on a ray of light as it travels through a medium [15]. Absorption and out-scattering attenuate radiance along the beam while emission and in-scattering increase it. These effects are caused by suspended particles in the atmosphere such as gasses, aerosols, and vapors. To develop the radiative transfer equation, we first introduce these processes. This discussion follows that of [15]. The following equations are applicable in any medium, however in this thesis the participating medium will always be the atmosphere.
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2.2.1 Volumetric Absorption and Out-Scattering

Absorption and out-scattering both attenuate radiance as a light ray passes through the atmosphere. When a photon collides with a suspended particle, it will either be scattered or absorbed. The photon will be absorbed according to the absorption cross section \( \sigma_a \). This absorption cross section describes the probability density that a photon will be absorbed per unit distance traveled through the atmosphere. It is highly dependent on wavelength; molecular species such as water, carbon dioxide, oxygen, and ozone are especially absorptive between certain wavelength bands. Figure 2.1 shows the extent of this atmospheric absorption in the VNIR-SWIR wavelengths by comparing solar irradiance incident to the top of the atmosphere (yellow) to irradiance at sea level (red). The molecular species responsible for creating each absorption band are labeled.

The absorption cross-section is also a function of position in the atmosphere \( x \) and the direction of light propagation \( \omega \). It provides a linear relationship between the radiance \( L_i \) incident to a differential ray length \( dt \) and the change in exitant radiance \( L_o \) from the volume due to particle absorption in that volume:

\[
\frac{dL_o(\omega; x, \lambda)}{dt} = -\sigma_a(\omega; x, \lambda)L_i(\omega; x, \lambda)dt \quad (2.4)
\]

If the photon collides with a suspended particle and is not absorbed, there is a chance that it will instead be scattered into a random direction. It is therefore scattered out of the current light.
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Ray in the radiance-reducing process called out-scattering. The scattering coefficient $\sigma_s$ determines the probability that a photon is out-scattered after it travels a unit distance through the atmosphere. As with absorption, the scattering coefficient provides a linear relationship between radiance incident to a differential volume and radiance lost due to out-scattering:

$$dL_o(\omega; x, \lambda) = -\sigma_s(\omega; x, \lambda)L_i(\omega; x, \lambda)dt$$  \hspace{1cm} (2.5)

The total radiance attenuation, denoted $\sigma_t$, over a differential volume is therefore the sum of the absorption cross section and scattering coefficient:

$$\sigma_t(\omega; x, \lambda) = \sigma_a(\omega; x, \lambda) + \sigma_s(\omega; x, \lambda)$$  \hspace{1cm} (2.6)

Expressing the total absorption and scattering coefficients in one term allows us to solve for the beam transmittance. We first express total differential radiance loss due to attenuation as

$$dL_o(\omega; x, \lambda) = -\sigma_t(\omega; x, \lambda)L_i(\omega; x, \lambda)dt$$  \hspace{1cm} (2.7)

The solution to this differential equation is the beam transmittance $\tau_r$. $\tau_r(x \rightarrow x')$ is defined between two points in the atmosphere, $x$ and $x'$, as:

$$\tau_r(x \rightarrow x', \lambda) = \exp \left( - \int_0^d \sigma_t(\omega; x + t\omega, \lambda)dt \right)$$  \hspace{1cm} (2.8)

where $d$ is the distance between the two points $x$ and $x'$. It represents the fraction of radiance that is transmitted between the points $x$ and $x'$ after taking into account attenuation. The total radiance $L_o$ leaving point $x$ is therefore related to the radiance $L_i$ arriving at point $x'$ through $\tau_r(x \rightarrow x')$:

$$L_i(\omega; x', \lambda) = \tau_r(x \rightarrow x', \lambda)L_o(\omega; x, \lambda)$$  \hspace{1cm} (2.9)

The transmittance has several important properties. When there are no particles to cause scattering or absorption, such as in a vacuum, $\sigma_t = 0$ and $\tau_r(x \rightarrow x') = 1$ for all points $x'$. Transmission of a point $x$ onto itself is always 1 and transmission is multiplicative along all points in a path. For points $x$, $x'$, and $x''$,

$$\tau_r(x \rightarrow x'') = \tau_r(x \rightarrow x')\tau_r(x' \rightarrow x'')$$  \hspace{1cm} (2.10)

As we will see in Section 2.3.3, this property is incredibly useful for modeling atmospheric transmission.
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2.2.2 Emission and In-Scattering

Where absorption and out-scattering remove photons from a ray of light traveling in the direction $\omega$ thereby decreasing radiance, emission and in-scattering add photons to that light ray, thus increasing radiance. Light is emitted by particles in the atmosphere due to thermal, nuclear, or chemical processes. Such emitted radiance, denoted $L_e$, is directly related to the change in exitant radiance over a differential ray length $dt$:

$$dL_0(\omega; x, \lambda) = L_e(\omega; x, \lambda)dt \quad (2.11)$$

We include this process for atmospheric emission for completeness; atmospheric emission is negligible in the VNIR-SWIR wavelengths in which we work throughout this thesis.

The other source of increased radiance for a light ray traveling through a differential ray length is in-scattering. In-scattered photons are photons that have been out-scattered from other light rays into the current one. Whereas the scattering coefficient $\sigma_s$ defines the probability that a photon will be scattered, the direction of scatter is defined by the phase function $p(\omega, \omega')$. Should a photon traveling in direction $\omega$ be scattered, the phase function $p(\omega, \omega')$ defines the probability that that photon will be scattered into direction $\omega'$. The complexity of this phase function depends upon the involved particles. The additional radiance gained by a light ray traveling in the direction $\omega$ over a differential ray length $dt$ from in-scattering can then be expressed as

$$dL_0(\omega; x, \lambda) = \sigma_s(\omega; x, \lambda) \int_{S^2} p(\omega', \omega; x)L_i(\omega'; x, \lambda)d\omega'dt \quad (2.12)$$

where the integral over $S^2$ integrates over all $4\pi$ steradians in a sphere. This equation says that the radiance gained from in-scattering is equal to the probability of scattering $\sigma_s$ multiplied by the amount of scattered light from all directions onto the current path $\omega$, as defined by the phase function.

Radiance contributions from both emission and in-scattering over a differential ray length can be combined to form a single source function $L_s$, such that

$$dL_0(\omega; x, \lambda) = L_s(\omega; x, \lambda)dt \quad (2.13)$$

where $L_s$ is defined to include the radiance contributions from both emission and in-scattering:

$$L_s(\omega; x, \lambda) = L_e(\omega; x, \lambda) + \sigma_s(\omega; x, \lambda) \int_{S^2} p(\omega', \omega; x)L_i(\omega'; x, \lambda)d\omega' \quad (2.14)$$

2.2.3 Equation of Transfer

The equation of transfer combines the radiance attenuation from absorption and out-scattering with the radiance contributions from emission and in-scattering into one equation that
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governs radiative transfer through the atmosphere. With total attenuation defined by the attenuation coefficient \( \sigma_t \) and total radiance contribution defined by the source function \( L_s \), the equation of transfer is defined as:

\[
\frac{\partial}{\partial t} L_o(\omega; x + t\omega, \lambda) = -\sigma_t(\omega; x, \lambda) L_i(\omega; x, \lambda) + L_s(\omega; x, \lambda) \tag{2.15}
\]

The equation of transfer simply states that the change in radiance experienced by a light ray as it travels through a differential ray length \( dt \) of the atmosphere is equal to the linear combination of radiance attenuation and addition over that volume.

For an infinite ray length that does not intersect any surface, (2.15) can be integrated to solve for incident radiance \( L_i \) to a location \( x \) along the ray:

\[
L_i(\omega; x, \lambda) = \int_0^\infty \tau_t(x' \rightarrow x) L_s(\omega; x', \lambda) dt \tag{2.16}
\]

This states that radiance incident to a point in the volume is the radiance contribution of all differential points along the ray between the point \( x \) and the ray’s origin, multiplied by the volume attenuation at all of those points. Despite this straightforward interpretation, solving the equation of transfer is extremely challenging: all molecular species along the traveled path must be characterized to estimate the radiance changes due to absorption, scattering, and emission; the phase function must be estimated for a given input radiance; and the equation must be solved numerically [3].

2.2.4 Surface Scattering

By solving the equation of transfer, we can determine how solar irradiance is altered as it travels from the top of the atmosphere to the ground, and again from the ground to a sensor. The last piece of the puzzle is to define how surface-incident radiance is converted by that surface to surface-leaving radiance. Such a function is called the Bidirectional Reflectance Distribution Function (BRDF). To define the BRDF, we start by defining the differential irradiance \( dE_i \) incident to a surface \( x \) in terms of the incident radiance \( L_i \) from the differential solid angle \( d\omega_i \). By differentiating (2.2), equating it to (2.3), and solving for irradiance, we have

\[
dE_i(\omega_i; x, \lambda) = L_i(\omega_i; x, \lambda) \cos \theta_i d\omega_i \tag{2.17}
\]

Note that irradiance is a directionless quantity; it is written here as a function of incident direction to reflect the illumination geometry. We are interested in the fraction of this irradiance that is reflected by the surface as radiance \( L_r \) into the observed direction \( \omega_o \). All objects are assumed to be
non-absorbing and all incident energy must be reflected by the surface. Since there must be a linear relationship between \( E_i \) and \( L_r \), the BRDF \( f_r \) is defined as the ratio of reflected radiance to incident irradiance [15]:

\[
f_r(\omega_o, \omega_i; x, \lambda) = \frac{dL_r(\omega_o; x, \lambda)}{dE_i(\omega_i; x, \lambda)} = \frac{dL_r(\omega_o; x, \lambda)}{L_i(\omega_i; x, \lambda) \cos \theta_i} \tag{2.18}
\]

and has units \( \text{sr}^{-1} \). Figure 2.2 illustrates the BRDF geometry. By rearranging (2.18) and integrating over all incident directions \( \omega_i \) in the northern hemisphere \( \mathcal{H}(n) \) with respect to the normal \( n \) of our surface \( x \), we can solve for the desired reflected radiance \( L_r \) in terms of the BRDF [15]:

\[
L_r(\omega_o; x, \lambda) = \int_{\mathcal{H}(n)} f_r(\omega_o, \omega_i; x, \lambda)L_i(\omega_i; x, \lambda) \cos \theta_i d\omega_i \tag{2.19}
\]

The significance of the BRDF is that it relates incident to reflected radiance over all viewing and illumination geometries. However, for each surface the BRDF is a continuous function of four variables (each direction \( \omega \) is a parameterization of azimuth and zenith angles \( \theta \) and \( \phi \), respectively) which is impossible to fully characterize [3]. We have also yet to relate the BRDF defined as a ratio of radiance to irradiance, to the reflectance, which is defined as a ratio of radiant fluxes. This challenge is addressed through one of the simplifying assumptions made during reflectance retrieval.

### 2.3 Traditional Reflectance Retrieval Methods

Given the definition of reflectance as the ratio of reflected to incident radiant flux from (2.1), reflectance retrieval methods must estimate lighting conditions at the target location as accurately
as possible. They therefore have the challenging task of solving the equation of transfer for light traveling from the top of the atmosphere to the target, and once again from the target to the sensor. The complete solution to the equation of transfer requires a full characterization of the scattering, absorbing, and emitting molecular species in the atmosphere; knowledge of the ground scene that surrounds the target, such that the spectral influences of background materials (e.g. grass) can be taken into account; and knowledge of illumination and observation geometries since reflectance is a directional quantity.

This complete reflectance retrieval solution requires an unobtainable amount of scene information, especially for near real-time conversion of HSI radiance to reflectance. The art of reflectance retrieval is to therefore determine what simplifying assumptions may be made without overly distorting the retrieved reflectance. A number of assumptions are traditionally employed by reflectance retrieval methods to make this problem more tractable [7]. These assumptions fall under into two categories: the Lambertian assumption which simplifies the target model, and target illumination assumptions that simplify atmospheric and light propagation modeling.

2.3.1 The Lambertian Assumption

A target is said to be Lambertian, or perfectly diffuse, if it reflects light equally in all directions at all possible illumination angles. Lambertian reflectors follow Lambert’s Law of Cosines:

$$\frac{d^2 \Phi(\lambda)}{dA d\omega} = L(\omega_i, \lambda) \cos \theta = L_d(\lambda) \cos \theta$$

(2.20)

where $L_d$ is a constant diffuse radiance reflected from the target [3]. This equation is equal to the definition of radiance from (2.3) when there is no dependence on observed direction $\omega_o$. When Lambert’s Law holds, the observed scattered radiance from an object is independent from viewing geometry; it changes only as a function of projected area. The Lambertian property is an idealization, but most matte surfaces can exhibit Lambertian behavior. Freshly fallen snow, charcoal, and unprocessed wood are all examples of nearly Lambertian natural materials [16].

Traditional reflectance retrieval models assume targets are Lambertian. Under the Lambertian assumption, we can relate the BRDF and reflectance. Since the BRDF is no longer dependent upon illumination direction $\omega_i$ and observation direction $\omega_o$, the diffuse BRDF $f_{r,d}$ simplifies to [3]

$$f_{r,d}(\lambda) = \frac{L_d(\lambda)}{E_i(\lambda)}$$

(2.21)
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Estimating the diffuse radiance $L_d$ and total incident irradiance $E_i$ is far more tractable than computing the full BRDF. Further, the diffuse BRDF can be related to diffuse reflectance $\rho_d$ through

$$\rho_d(\lambda) = \frac{d\Phi_r(\lambda)}{d\Phi_i(\lambda)} = \pi f_{r,d}(\lambda)$$

(2.22)

Diffuse reflectance is therefore expressed as

$$\rho_d(\lambda) = \frac{\pi L_d(\lambda)}{E_i(\lambda)}$$

(2.23)

As a result of the Lambertian assumption and (2.23), reflectance estimation becomes the relatively more straightforward problem of estimating the diffuse radiance leaving the target and the irradiance incident to the target.

2.3.2 Illumination Assumptions

Traditional reflectance retrieval methods make three assumptions regarding scene illumination. First, it is assumed that the target is illuminated only by direct sunlight and scattered skylight. This prevents the scene from having bright light sources that would unpredictably illuminate the target. Second, the sky must be free of clouds. This prevents clouds from shading the target and simplifies light propagation models through the atmosphere. Finally, it is assumed that the target exists in an open environment. Traditional methods are not equipped to model increased or decreased illumination from buildings or vegetation. Implicit in these assumptions is the requirement that all surfaces in the target scene are illuminated evenly \[7\]. When these assumptions are valid, reflectance retrieval via atmospheric compensation alone provides acceptable results.

2.3.3 Atmospheric Compensation

The diffuse radiance and irradiance in (2.23) are ground-level quantities which must be estimated from measured at-sensor radiance and known solar irradiance, respectively. Figure 2.3, repeated here from Figure 1.3, shows how the atmospheric transmission loss and surface reflection alter solar irradiance as it travels from the top of the atmosphere, to the target, and on to the sensor. We would like to retrieve the shown target reflectance spectrum using the measured at-sensor radiance and known solar irradiance. To do so, the atmospheric effects on these quantities must be estimated. Atmospheric compensation codes, such as MODerate resolution atmospheric TRANsmission\textsuperscript{®} (MODTRAN), solve the equation of transfer to derive these ground-leaving quantities. MODTRAN\textsuperscript{®} solves the equation of transfer using a provided atmospheric model. This
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model partitions the atmosphere into a series of discrete layers. Each layer has its own distribution of molecular species, with its own total attenuation parameter $\sigma_t$, scattering phase function $p$, emitted radiance $L_e$. The advantage of modeling the atmosphere as a series of layers is that the transmission through each layer can be calculated individually, such that the total transmission through the atmosphere is defined by (2.10). These discrete layers will accurately model the atmosphere when clouds are not present, as clouds can cause mixing between layers. A vital part of atmospheric compensation is therefore the proper estimation of molecular species present in each layer of the local atmosphere, which informs the total attenuation parameter $\sigma_t$, and scattering phase function $p$, and the emitted radiance $L_e$ for each layer in the model. These parameters can be derived either from atmospheric measurements or from HSI data itself [3].

While Figure 2.3 illustrates the atmospheric effects on radiance, the direct path shown between the solar irradiance, target, and sensor is but one radiance path that contributes to the overall

Figure 2.3: The path of solar radiance as it travels from the top of the atmosphere, to the ground-level surface, and finally to the sensor. At each step of the path, the incident solar radiance spectrum is altered by the environment, either through atmospheric transmission or surface reflection [2]. This figure is repeated from Figure 1.3.

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Figure 2.4: The five assumed sources of measured radiance for any given HSI pixel.

radiance that is measured by the sensor. Under the previously mentioned assumptions, measured at-sensor radiance $L_{as}(\lambda)$ is composed of five constituent sources. These sources can be grouped into two categories. The first is radiance that is reflected off of the target and into the sensor’s Field of View (FOV). This includes the direct sunlight $L_s(\lambda)$ that reaches the target; radiance that is scattered by the atmosphere onto the target $L_{at}(\lambda)$; and radiance $L_{gt}(\lambda)$ that is scattered off of the ground, back to into the atmosphere, and finally onto the target. The second category is radiance that is indirectly scattered into the sensor’s FOV without first reaching the target. This category includes the diffuse atmospheric path radiance $L_{ad}(\lambda)$ and radiance $L_{gd}(\lambda)$ that is scattered off of the ground and into the sensor. These radiance sources are illustrated in Figure 2.4.

Measured at-sensor radiance is the sum of these radiance contributions [3]:

$$L_{as}(\lambda) = L_s(\lambda) + L_{at}(\lambda) + L_{gt}(\lambda) + L_{ad}(\lambda) + L_{gd}(\lambda)$$ (2.24)

In order to convert measured at-sensor radiance to the desired target ground-leaving radiance, indirect radiance contributions, $L_{ad}(\lambda)$ and $L_{gd}(\lambda)$, must be removed and atmospheric transmission loss on the radiance contributions from the target, $L_s(\lambda)$, $L_{at}(\lambda)$, and $L_{gt}(\lambda)$, must be taken into account. Atmospheric transmission losses must also be estimated to convert the solar irradiance, which is known above the atmosphere, to ground-incident radiance.

During atmospheric compensation, the indirect radiance contributions are parameterized as the path radiance $L_p(\lambda)$ and the atmospheric transmission losses are parameterized as transmittance $\tau(\lambda)$. With these parameters, at-sensor radiance is linearly related to ground-leaving
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radiance $L_t(\lambda)$:

$$L_{as}(\lambda) = \tau(\lambda)L_t(\lambda) + L_p(\lambda)$$  \hspace{1cm} (2.25)

This equation can be inverted to solve for target-leaving radiance, which is assumed to be the Lambertian radiance $L_d(\lambda)$

$$L_d(\lambda) = \frac{L_{as}(\lambda) - L_p(\lambda)}{\tau(\lambda)}$$  \hspace{1cm} (2.26)

The parameters $L_p(\lambda)$ and $\tau(\lambda)$, as well as the needed surface-incident irradiance, are estimated using atmospheric correction programs such as MODTRAN® [17]. It uses a given scattering and absorption model to solve the radiative transfer equations for light rays traveling along the paths outline in Figure 2.4. This entails calculating direct and diffuse radiance. Diffuse radiance includes light that has reflected off of the ground, back to the atmosphere, and to the target, or the light that is reflected off of the ground and directly into the sensor’s FOV. For these ground reflections, a so called adjacency reflectance is used. This adjacency reflectance is commonly assumed to be the averaged background reflectance of the target scene [3]. Once ground-incident radiance has been calculated at the target for every solid angle, ground-level irradiance can be determined by integrating the incident radiance over every solid angle in the upper hemisphere [3]:

$$E_i(\lambda) = \int_{\mathcal{H}(n)} L_i(\omega, \lambda) \cos \theta_i d\omega_i$$  \hspace{1cm} (2.27)

This irradiance calculation is valid under the assumption that all atmospheric radiance entering the scene, as predicted by MODTRAN®, reaches the target. This reinforces the open-environment assumption made by traditional reflectance retrieval methods.

When given measured radiance and solar irradiance, atmospheric compensation techniques will often solve for reflectance directly. Under the Lambertian assumption, diffuse reflectance can be expressed as [7]

$$\rho_d(\lambda) = \frac{\rho_{ac}(\lambda)}{1 + \rho_{ac}(\lambda)s(\lambda)}$$  \hspace{1cm} (2.28)

where

$$\rho_{ac}(\lambda) = \frac{L_{as}(\lambda) - L_p(\lambda)}{E_o(\lambda) \cos \theta_\text{s} \tau_\text{s}(\theta_v, \lambda) \tau(\theta_v, \lambda)}$$  \hspace{1cm} (2.29)

and $E_o(\lambda)$ is the incident solar irradiance, $\tau_\text{s}(\theta_v, \lambda)$ is the transmission from the sun to the ground, $\tau(\theta_v, \lambda)$ is the sum of the direct and diffuse transmissions to the sensor, and $s(\lambda)$ is the spherical albedo of the atmosphere. Like before, this assumes and open environment that will not alter the path of scene-incident light before it reaches the target.
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2.4 Hyperspectral Data Processing

This calculated reflectance is used for HSI target detection and material classification algorithms. For these algorithms, the entire HSI image cube is converted from radiance to reflectance. When working with these reflectance signatures, each pixel in the data cube is treated as a vector \( \mathbf{x} = [x_1, x_2, \ldots, x_K]^T \) in \( K \)-dimensional Euclidean space. The basis of HSI data exploitation is quantifying the similarity between spectral reflectance vectors. For vectors \( \mathbf{x} \) and \( \mathbf{y} \), two commonly used similarity metrics are the Euclidean distance and the Spectral Angle Map (SAM) [2]. The Euclidean distance metric is defined as

\[
\| \mathbf{x} - \mathbf{y} \| = \sqrt{\sum_{k=1}^{K} (x_k - y_k)^2} \tag{2.30}
\]

Spectra \( \mathbf{x} \) and \( \mathbf{y} \) will be considered similar if their Euclidean distance is small. This metric is not robust to illumination changes that cause magnitude differences in compared spectra. Even if spectra \( \mathbf{x} \) and \( \mathbf{y} \) have similar shapes, if they have varying magnitudes their Euclidean distance will be high. To mitigate this, the SAM metric can be used. The SAM metric compares the spectral shapes of \( \mathbf{x} \) and \( \mathbf{y} \). It is defined as [2]

\[
\angle(\mathbf{x}, \mathbf{y}) = \arccos\left( \frac{\mathbf{x}^T \mathbf{y}}{\|\mathbf{x}\| \|\mathbf{y}\|} \right) \tag{2.31}
\]

and computes the angle between spectra \( \mathbf{x} \) and \( \mathbf{y} \). Spectra are considered similar if their SAM metric is small. By using spectral shape as a similarity metric, SAM is immune to spectral magnitude changes. Note that neither the Euclidean distance nor SAM metrics have classification thresholds associated with them. It is up to the detection algorithm to set an appropriate threshold that maximizes the chance of target detection or classification while minimizing the false alarm rate [14].

Target detection is often done by matching measured spectra to that of targets in a spectral library [14]. This means detection algorithms perform optimally when measured spectra closely match their spectral library counterpart in shape and amplitude. Since HSI sensors measure radiance, it is simplest to run detection algorithms in the radiance domain. Some algorithms, such as in [13], have had moderate success at this. However, classification in the radiance domain is difficult. While measured radiance does in part depend on the target composition, as previously described it also depends on extrinsic factors such as illumination and atmospheric conditions. As a result, identical targets imaged under varying lighting conditions will not have identical radiance spectra and can therefore be misidentified. However, this does once again highlight the importance of accurately estimating target illumination conditions during reflectance retrieval. Even seemingly small errors in
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estimated illumination can lead to large errors in the retrieved reflectance, and therefore poor spectral exploitation.

2.5 Reflectance Retrieval for Urban Environments

An immense number of factors affect target-incident irradiance and target-leaving radiance, including but not limited to solar illumination, local atmospheric scattering and absorption, target environment, illumination angle, and observation angle. The simplifying assumptions made by traditional reflectance retrieval methods make the reflectance retrieval tractable, but limit its solution space to certain environments. Urban environments are particularly challenging for traditional reflectance retrieval algorithms because they violate the open-environment assumption. Atmospheric compensation methods are not equipped to model how light propagates through an urban scene before it reaches a target. This section first explores how violation of the open-environment assumption causes reflectance retrieval to fail. We then introduce a solution to the problem of reflectance retrieval in urban environments.

2.5.1 Challenges of Urban Environments

In an urban scene, the open-environment assumption is invalid under two simple cases: indirect and obscured illumination. Figure 2.5 illustrates both of these cases. Under the presence of indirect or obscured illumination, traditional reflectance retrieval methods are unable to accurately predict target-incident irradiance. This results in distorted reflectance spectra and poor spectral library matches under both the Euclidean distance and SAM metrics, which in turn decreases the performance of target detection and material classification algorithms.

In cases of indirect illumination, the target is illuminated by direct and scattered sunlight as expected by the open environment assumption. However, it also receives indirect illumination from light reflected off of surrounding objects. Two things happen when the target is indirectly illuminated by an object. First, that object blocks the line of sight between the target and a section of the atmosphere. This means that less scattered atmospheric light reaches the target. From this, we expect the overall radiance to decrease. Second, the blocked atmospheric light is replaced by light that has been reflected off of the object. This in turn brightens the target. Furthermore, this indirect illumination imparts onto the target the spectral characteristics of the reflecting object. The combination of blocking atmospheric light and replacing it with indirectly reflected light causes the
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Figure 2.5: Examples of indirect and obscured illumination (left and right panels, respectively). In cases of indirect illumination, the target receives additional illumination from surrounding objects. In cases of obscured illumination, surrounding objects block light from reaching the target.

target to appear brighter and spectrally different than it would if the open environment assumption were valid. In the indirect illumination case, traditional reflectance retrieval methods would therefore overestimate and distort the target reflectance.

In the case of obscured illumination, the target is no longer illuminated by direct sunlight as expected under the open-environment assumption. Instead, the target is only illuminated by sunlight scattered off of the atmosphere. Furthermore, the target receives less atmospheric illumination than an open-environment target would because the obscuring object blocks a significant portion of scattered atmospheric illumination from reaching the target. Just as in the indirect illumination case, some reflected light from the building will reach the target, however we expect this influence on target radiance to be small due to the low lighting conditions. The target therefore appears darker than expected under the open-environment assumption. In the obscured illumination case, traditional reflectance retrieval methods would therefore underestimate and distort target reflectance.

In both cases, the lack of proper illumination models will cause traditional reflectance retrieval methods to produce a reflectance that differs greatly from corresponding targets in spectral libraries. The resulting Euclidean distance and SAM metrics will be large and will greatly increase the probability of target misclassification.
2.5.2 Method for Urban Reflectance Retrieval

A method for urban reflectance retrieval was introduced in [7]. It is suitable for urban environments and does not depend upon the open-environment assumption. By fusing HSI data with known scene geometry information, it is able to account for the complex illumination conditions found in urban environments. As in traditional methods, it first uses atmospheric compensation to convert measured at-sensor radiance to surface-leaving radiance and known solar irradiance to scene-incident irradiance. It then use knowledge of localized scene geometry to estimate how this radiance propagates throughout our scene before it reaches a target. This provides an illumination correction to the atmospherically-compensated scene-incident irradiance which accounts for instances of obscured and indirect illumination. Figure 2.6 shows the flowchart for this process. While this method does not require open-environments, it maintains the other assumptions made by traditional reflectance retrieval methods: all surfaces in the scene are assumed to be Lambertian, the scene must be illuminated only by sunlight and scattered skylight, and the atmosphere must remain cloudless.

Accurate scene geometry information is paramount to the success of this method. Three scene geometry problems must be solved for successful urban reflectance retrieval. The first problem is that of geometry acquisition. Scene geometry must be measured and converted into a 3D mesh suitable for use with computer rendering algorithms. Several techniques exist for generating 3D meshes of a target scene. Researchers in [9] had success creating a geometry model with measured LADAR data. RIT also had success with this during the SHARE collection campaigns [10][11]. LADAR sensors produce geo-located point clouds which are then converted into 3D meshed geometric models. Another method for mesh construction utilizes high-resolution 2D imagery taken of the scene from multiple look-angles. 3D geometry can be extracted from these images by correlating the

Figure 2.6: Flowchart of our proposed reflectance retrieval method for urban environments.
CHAPTER 2. BACKGROUND

locations of corresponding features. The second problem is that of meshing acquired scene geometry. This process must take the acquired 3D point cloud and convert it into a coherent mesh suitable for use with computer rendering algorithms. Lastly, this mesh must be segmented into its constituent surfaces. This can be accomplished algorithmically by the method outlined in [13]. Each one of these surfaces must then be assigned an appropriate spectral reflectance such that accurate light reflections off of each surface can be modeled.

With the mesh generated, segmented, and reflectance spectra assigned, the scene model must be co-registered to the measured HSI data. The accuracy of this co-registration step has an tremendous effect on reflectance retrieval performance. Once registered, at-sensor HSI radiance is converted to ground-leaving radiance via (2.26). Each pixel of this ground-leaving radiance data is mapped to each individual facet of the scene model. A ray tracing algorithm then solves the localized light transport to estimate the illumination-corrected irradiance incident to every facet. With target-incident irradiance and target-leaving radiance known, the Lambertian reflectance can be calculated with (2.23).

Fusing HSI data with a scene geometry model provides the opportunity for not just reflectance retrieval, but at-sensor radiance estimation, as was done by RIT in [13]. While reflectance retrieval is our ultimate goal, in this thesis we will employ a forward radiance estimation model to evaluate the performance of such a model in urban environments. Estimating at-sensor radiance allows us to verify the accuracy of generated scene geometry, measured ground-truth data, atmospheric models, and the localized ray tracing technique. It further provides the opportunity to study how light propagates throughout an urban environment. We will therefore use this forward model for the performance evaluation done in this thesis. Once this is done, we will then show initial reflectance retrieval results.

2.6 Summary

Reflectance retrieval is an incredibly challenging problem. A complete solution to this problem would require full knowledge of atmospheric scattering, absorption, and emission effects and full knowledge of the ground scene geometry, including reflectance properties for all objects at every illumination and observation geometry. To make this problem tractable traditional methods make simplifying assumptions about the target and scene illumination. These assumptions assert that illumination is constant over the entire scene, allowing reflectance to be retrieved through atmospheric compensation alone. Traditional methods produce accurate reflectance estimates when
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the assumed conditions are valid. Using these results, the Euclidean distance or SAM metrics will likely lead to accurate target detection or material classification. When assumed conditions are not present, however, retrieved reflectance and the resulting spectral exploitation will be inaccurate. This is the case in urban environments, where the open-environment assumption is violated.

In this thesis, we utilize a solution to reflectance retrieval in urban environments that fuses HSI data with a scene geometry model. This model contains spatial information about the targeted urban scene as well as reflectance information for each object within that scene other than the target. The addition of scene geometry allows ray tracing algorithms to model how the atmospherically-corrected radiance propagates throughout the scene before it reaches the target. This illumination-corrected irradiance and its corresponding atmospherically-corrected measured HSI radiance is then used for reflectance retrieval. Model performance evaluation is a necessary step to understand the strengths and weaknesses of this method. In this thesis, we will evaluate the performance of this method by using it to estimate measured radiance data. We will describe the data used for this thesis in Chapter 3. Adjoint Radiosity provides the basis for the urban reflectance retrieval method utilized in this thesis.
Chapter 3

Data Collection Campaign

This thesis utilizes data taken during a collection campaign which was designed to collect the scene geometry, material reflectance, and atmospheric data required to develop the urban environment reflectance retrieval method. This was accomplished through airborne and ground-based data collection efforts. While this work addresses the open-environment assumption, this method still assumes that the target scene receives constant atmospheric and solar illumination and that the atmosphere is free of clouds. As such, the data collection day was required to have clear sky conditions. A successful data collect was completed on the morning of October 7, 2016, when conditions were most favorable to these model assumptions. During this data collect, the sun illuminated the scene from the southeast with elevation angles between 17 and 38 degrees.

In Section 3.1, we first describe the chosen test environment, the illumination conditions they create, and describe the expected behavior of each target. Next, Section 3.2 describes the data collection procedure, including a brief description of sensors used and both flight and ground operations. Finally, Section 3.3 summarizes these data collection efforts.

3.1 Urban Test Environments

An office complex in the greater Boston area was selected as the target scene for the data collection campaign. This office complex was partitioned into two scenes of varying illumination complexity. Within each scene, a number of near-Lambertian colored targets were arranged in open, obscured, and indirect lighting conditions. Here we first describe the expected reflectance behavior of these targets, followed by descriptions of these two test scenes and the illumination conditions we expect targets to experience within them.
CHAPTER 3. DATA COLLECTION CAMPAIGN

3.1.1 Target Reflectance Characteristics

The targets consisted of square tarps of various sizes and colors arranged throughout the urban test scene. The primary targets were red and white engineering tarps, 3 meters on a side. In addition, one larger red and one blue engineering tarp, 6 meters on a side, were used. All tarps were manufactured to be near-diffuse reflectors. This is crucial for the Lambertian assumption made during reflectance retrieval. The red tarp effectively black in the blue and green wavelengths, the blue target is reflective in the blue wavelengths, effectively black in the green and red wavelengths, and evenly reflective in the VNIR-SWIR. The contrast between these targets in the visible wavelengths is important for differentiating between direct solar and diffuse atmospheric illumination.

3.1.2 Primary Target Scene

The simplest of the two areas in the office complex was chosen to be the primary test scene. A 3D Computer-Aided Design (CAD) model depicting the complete layout of this scene is shown in Figure 3.1. This scene was arranged around a single three story office building adjacent to two grassy fields; one north and one south of the building. The northern field is completely open and has a gentle slope between the building and the road. The southern field is cut by a utility road near the building, and is framed on four sides with the building to the north and trees of varying height to the east, west, and south. This geometry forms what is known as an urban canyon, in which targets are simultaneously shaded by buildings (or trees in this case) on one side of the canyon and indirectly illuminated by buildings on the other side [7].

Targets were placed throughout the scene such that at least several targets experienced indirect, obscured, or relatively open lighting conditions. They are labeled in Figure 3.1. During the morning data collection, the south face of the building was sunlit. The three red and three white 3 × 3 meter targets to the south of the building experienced indirect illumination from the building facade and windows and partial obscured illumination during the early morning from the surrounding trees. The three red and three white 3 × 3 meter targets directly north of the building experienced obscured illumination during the morning data collections. The building’s shade line receded as the morning progressed such that the outermost red and white targets were partially sunlit at the end of the data collection. One 6 × 6 meter red target was placed in the open field further from the building. Here, this target experienced illumination conditions similar to those expected by traditional reflectance retrieval algorithms: no indirect or obscured illumination from a building. It can therefore be used as a ground truth test case for the urban reflectance retrieval method since the method should agree with
CHAPTER 3. DATA COLLECTION CAMPAIGN

To further study the effects of indirect illumination, two walled structures were constructed. They are shown in Figure 3.2. These structures consisted of a vertical red $3 \times 3$ meter target held in place by a metal frame. They were placed adjacent to white $3 \times 3$ meter targets, where the spectral influence of the red walls would be easily visible. One such red and white target setup was placed in

Figure 3.1: 3D CAD model of the primary target scene. All targets are labeled in the top image.
CHAPTER 3. DATA COLLECTION CAMPAIGN

the northern field away from the building and the other was placed against the southern sunlit side of the building. The targets used in these wall structures were identical to the other smaller red and white targets elsewhere in the target scene.

Figure 3.2: Close up views of the two red wall and white target structures placed in the primary test scene. At left is the wall structure in the north field. At right is the wall structure built onto the south side of the building.

3.1.3 Secondary Target Scene

The secondary test scene was chosen to study lighting conditions more complex than those found in the primary scene. It was arranged around two buildings to the north and east of a central field, and a wooded field to the south. A 3D CAD model of this scene is shown in Figure 3.3. The eastern building is tall and rectangular with flat walls and a flat roof. It has facade of brown brick and is therefore known as the brown building. The northern building is less than half the height of the brown building. It has a sloped roof and faded yellow corrugated metal walls. It is therefore known as the yellow building. The yellow building extends north of the brown building to form a narrow L-shaped canyon that is fully shaded throughout the morning. To the south, the trees in the southern wooded field shade the a portion of the central field in the mornings and to an extent, the brown and yellow buildings. A road lies to the west of the central field, across of which is another field with more trees.

Two targets were placed in this secondary scene. The first target is a $3 \times 3$ meter red tarp placed in the middle of the central field. This target is shaded by the trees to the southeast in the early morning and is sunlit during the late morning. It additionally receives some indirect illumination from the yellow building. The second target is a cube, 1.5 meters on a side. It is placed in the urban canyon formed by the east face of the yellow building and west face of the brown building. A detailed view of the cube is shown in Figure 3.4. The cube itself is shaded for the duration of the morning,
CHAPTER 3. DATA COLLECTION CAMPAIGN

however its top face is indirectly illuminated by both the yellow and brown buildings and its front face receives indirect illumination from the yellow building and grass. In addition, we expect sunlit grass to reflect light onto the yellow building and then to the cube, and the sunlit yellow building to reflect light onto the brown building wall and then to the cube. Emulating these conditions will be the toughest challenge for the model.

Figure 3.3: 3D model of the secondary urban target scene. Targets are labeled in the top image.
CHAPTER 3. DATA COLLECTION CAMPAIGN

Figure 3.4: Detailed view of 3D cube target between the yellow and brown buildings.

3.2 Data Collection Methods

The data collection campaign consisted of two simultaneous collection efforts: one airborne collect to measure HSI data and scene geometry information and one ground-based collect to characterize the ground scene. This characterization included measuring atmospheric aerosol content to facilitate atmospheric compensation and ground-leaving radiance and reflectance measurements for the targets in the test scenes. The data collect started in the early morning to maximize the chances of clear skies throughout the entire campaign.

3.2.1 Flight Operations

The aircraft carried a single integrated optical bench on which was mounted a sensor suite. Three sensors were flown: an HSI, LADAR, and panchromatic context camera. The HSI sensor was a whisk-broom sensor that operated in the VNIR-SWIR. Its design was based upon the COMPact Airborne Spectral Sensor (COMPASS) system [19]. The LADAR sensor operated at roughly 1000nm. It utilized a two-axis scan mirror to lock on one location during an entire flight pass, enabling data to be taken of both the rooftops and sides of buildings. The context camera had a resolution of 5 megapixels and its focal length was chosen to cover an area just larger than the area covered by a single HSI whisk. All measured data was geo-located via an onboard Inertial Measurement Unit / Global Positioning System (IMUGPS). The optical bench was mounted on the floor of the aircraft just above a view-port to provide the sensors with nadir-looking lines of sight.

The flight consisted of a series of passes that viewed the target scenes from a number of look-angles to ensure both the sides and tops of buildings could be imaged. These included nadir, off-nadir, and semi-circular banked passes. Flight passes were organized by type and flown in
alternating groups such that all targets were imaged multiple times at each look angle. This allowed us to image each target at each look angle over the changing illumination conditions as the solar elevation increased over the course of the morning.

3.2.2 Ground Operations

The ground collection team collected atmospheric and in-situ target radiance measurements. The atmospheric measurements supported the development of localized atmospheric models for the collection day. The target radiance measurements were used to calculate target reflectance factors, which are in turn used as estimates for apparent target reflectance under the environmental conditions of the data collect. These reflectance spectra are crucial for HSI radiance modeling and urban reflectance retrieval.

Two rooftop Automated Solar Radiometer (ASR) s were used to measure the direct solar and diffuse atmospheric radiance for the duration of the data collection. From these measurements, the molecular and aerosol content of the atmosphere can be derived to develop atmospheric scattering and absorption models localized to the test environment. These models provide the necessary parameters to estimate atmospherically-corrected radiance values using the equation of transfer (2.15). The measured diffuse atmospheric radiance is further used as ground-truth for determining the accuracy of the derived atmospheric models. A detailed description of ASR operation can be found in [20].

Meanwhile, the ground collection team took surface-leaving radiance measurements of all objects within the target scenes: targets, buildings, and a representative sample of grass and asphalt. One set of eight measurements was taken per target. These measurements were taken with a calibrated Analytical Spectral Devices (ASD) spectroradiometer (also known simply as the [ASD]). For each measurement, the [ASD] was placed directly over the target and away from edges. Before and after the eight target radiance measurements were taken, the radiance from a reference panel was measured. We used a Spectralon® reference panel, which is manufactured to have a constant Lambertian reflectance of 99% [21]. The panel was placed adjacent to the target, such that each experienced identical lighting conditions. By measuring radiances of the target and the Lambertian reference panel, the target’s reflectance factor $R(\lambda)$ was calculated. The reflectance factor is defined as the ratio of measured target radiance $L_t(\lambda)$ to measured Lambertian reference panel radiance $L_{ref}(\lambda)$ [3]

$$R(\lambda) = \frac{L_t(\lambda)}{L_{ref}(\lambda)}$$  \hspace{1cm} (3.1)
and is an estimate of the target’s apparent BRDF under the given lighting conditions. The reflectance factor is only truly valid under the viewing and illumination conditions in which it was measured. However, under the Lambertian assumption used by the model, it is a good approximation for a target’s diffuse reflectance $\rho_d(\lambda)$ \[3\].

Since reflectance factor is the ratio of two values, absolute ASD calibration is not necessary. However, since the ASD was calibrated, its measured radiance data is accurate and proved to be extremely useful for model performance evaluation.

### 3.3 Summary

A successful data collect was completed over two urban test scenes during the morning of October 7, 2016. This collection day had a clear sky to satisfy the atmospheric compensation assumptions made by the model we use in this thesis. Airborne HSI, LADAR, and panchromatic imagery were collected from multiple viewing angles while a ground team collected atmospheric data, ground-leaving radiance and reflectance factor measurements of the targets and background materials in the two test scenes. The primary collection site consisted of a single building around which we placed red and white targets. These targets experienced either open, indirect, or obscured lighting conditions, all of which are common in urban settings. The secondary test site consisted of a number of buildings and trees that created illumination conditions more challenging than those found in the primary test site. The main target in this site was a white cube placed between the two buildings in what is known as an urban canyon. The overarching goal of this thesis will be to use this collected data to validate and analyze an urban light propagation model which can be applied to urban reflectance retrieval or radiance estimation.
Chapter 4

Simulation Methods

As we discussed in Section 2.5.2, the solution to urban reflectance retrieval used in this thesis utilizes a generated scene geometry model to provide an illumination correction to atmospherically-compensated scene-incident irradiance. Successful urban reflectance retrieval requires that this model accurately describes the true scene geometry and spectral properties of materials in the scene. When these requirements are satisfied, light propagation throughout the scene can accurately be estimated to determine true target incident irradiance. For reflectance retrieval, this irradiance must then be paired with the correct pixel in the measured HSI image cube. In addition to atmospheric models, such a simulation therefore requires this described accurate scene geometry model, a co-registration method to map measured HSI data to this scene geometry, and an accurate method for modeling how light propagates throughout the model.

In this chapter we present the methodology and simulation framework for solving the urban radiance estimation and reflectance retrieval problems. This method builds upon that presented in [7]. Where the method in [7] uses the radiosity equations to estimate light transport, the method used in this thesis solves the light transport equation and is primarily designed for radiance estimation. Section 4.1 describes our method for generating accurate facetized scene geometry models. Section 4.2 then describes our technique for co-registering our scene models with our measured HSI data. In Section 4.3 we introduce the rendering equation and derive its simplified form, which is valid under the Lambertian assumption. Section 4.4 describes the computational tools we use for atmospheric compensation and ray tracing as well as our framework for simulating radiative transport throughout urban environments. Finally, 4.6 summarizes our approach to radiance estimation and reflectance retrieval in urban environments.
CHAPTER 4. SIMULATION METHODS

4.1 Scene Model Generation

During the data collect described in Chapter 3, co-collected HSI, LADAR, and panchromatic imagery were collected with the intention of using the LADAR and panchromatic imagery to generate 3D models of our target scenes. The LADAR data product is a point cloud, where each point represents the distance of the reflecting object to the sensor. This raw data is geolocated based upon platform IMUGPS measurements. Multiple geolocated scans taken from various viewing angles are then combined to form a complete geolocated point cloud of the scene that includes vertical and horizontal surface geometry. Further processing converts this point cloud to a facetized mesh, which is then segmented by material such that the appropriate reflectance factor measurements may be assigned to each facet. Scene geometry can also be extracted from panchromatic imagery taken of our scene from multiple vantage points. Corresponding features are selected from each image. Based on the pixel locations of matching features in each image, the coordinate in 3D world space that corresponds to that feature can be determined. This triangulation process is repeated for thousands of matched image features to create a 3D point cloud of the scene. As with the LADAR data, this point cloud is geolocated with platform IMUGPS measurements and converted into a facetized mesh. Each facet is then assigned the appropriate reflectance factor measurement.

Meshes from LADAR or panchromatic imagery can be algorithmically generated, but the resulting geometry and segmentation is inevitably imperfect. These imperfections can add confounding errors to our radiance and reflectance retrieval results. To eliminate geometry and material segmentation errors while developing our methods, we have opted to build our scene models by hand using the open-source modeling program Blender [23]. Overhead views of the Blender models for our primary and secondary test scenes are shown in the left and right panels of Figure 4.1, respectively. As with the meshes created from our measured data, these hand-crafted scenes are composed of facets. However unlike the facets in the other meshes, these facets are perfectly segmented by material and separate materials have crisp boundaries, therefore minimizing geometry-related errors in our modeling.
4.2 HSI and Scene Model Co-Registration

HSI and scene model co-registration is a necessary pre-processing step that dictates the success of reflectance retrieval. Co-registration finds the optimal transformation between the world coordinates in which the scene model is based and the HSI camera coordinates. This transformation maps facets in our scene model to the pixels in the HSI image to facilitate radiance estimation, and the inverse transformation projects HSI pixels onto the scene model facets to facilitate reflectance retrieval. Inaccurate co-registration would cause HSI pixels to be mapped to the wrong ground locations. This causes a mismatch between measured target radiance and estimated irradiance and therefore inaccurate reflectance retrieval. Accurate co-registration is especially important for small targets that constitute low numbers of pixels in the HSI image.

The camera model that maps the 3D world coordinate \([x \ y \ z]\) to the 2D HSI spatial pixel coordinate \([u \ v]\) takes the following form in homogeneous coordinates:

\[
\omega \begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix} = K_{3\times4} \times R_{4\times4} \times T_{4\times4} \times \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \tag{4.1}
\]

where \(\omega\) is a scaling constant, \([u' \ v']\) is the world coordinate \([x \ y \ z]\) represented in HSI image coordinates, \(K_{3\times4}\) is the intrinsic matrix for the HSI camera, \(R_{4\times4}\) is a rotation matrix, and \(T_{4\times4}\) is a translation matrix. To map the point \([x \ y \ z]\) in world coordinates to the point \([u' \ v']\) in HSI image coordinates, \(T\) translates the point to the location of the HSI camera, \(R\) rotates the translated point such that the axes of its coordinate system coincide with the axes of the HSI coordinate system, and
CHAPTER 4. SIMULATION METHODS

K projects this rotated and translated point onto the HSI image plane to yield the point \([u' v']\) in HSI pixel coordinates.

The translation governed by \(T\) and rotation governed by \(R\) are functions of extrinsic camera parameters, while the projection onto the HSI image plane in \(K\) is a function of intrinsic camera parameters. Examples of extrinsic parameters include platform location and orientation; examples of intrinsic parameters are camera focal length and focal plane offset [24]. These parameters, collectively defined as the vector \(\phi\), represent physical properties of the system and may deviate slightly from known initial values during flight. The co-registration process therefore must determine the parameter vector \(\hat{\phi}\) that optimally maps 3D world coordinates to 2D HSI pixel coordinates. This is done by manually choosing tie points between the ground scene and the HSI image. Tie points are ideally prominent features in the target scene such as building corners. We define a tie point pair as the point \(p_w = [x y z]\) in world coordinates and the point \(p_c = [u v]\) in HSI image coordinates. The point \(p'_c = [u' v']\) is then the point \(p_w\) mapped into HSI image coordinates according to Equation 4.1.

The optimal parameter vector \(\hat{\phi}\) will minimize the squared distance between all HSI tie points \(p_c\) and their corresponding world coordinates mapped to HSI image coordinates \(p'_c\):

\[
\hat{\phi} = \arg \min_{\phi} \sum_{n} \|p_{c,n} - p'_{c,n}(\phi)\|^2 \tag{4.2}
\]

where

\[
\omega p'_c(\phi) = K(\phi)R(\phi)T(\phi)p_w \tag{4.3}
\]

defines the mapped HSI pixel location as a function of \(\phi\) and \(\omega\) is the scaling constant from Equation 4.1.

By optimizing over this parameter space, we are able to map world coordinates \(p_w\) to within 1 pixel of their corresponding pixel locations \(p_c\) in the HSI image. This accurate mapping means that measured target radiance from our HSI sensor can be paired with estimated irradiance from the target’s correct location within our scene model. We can therefore have confidence that our radiance estimation and reflectance retrieval results will not be inaccurate due to spatial misregistration between our target scene model and the HSI image.

4.3 Scene Rendering

Scene rendering is the process of calculating the surface-leaving radiance of every facet in our modeled urban scene. This process is the forward model; solving it requires the scene geometry
model, all material BRDFs, and atmospheric scattering and absorption to be fully characterized. With these quantities known, the radiative transfer and surface scattering equations defined in Section 2.2 can be solved to accurately calculate the desired surface-leaving radiance at every facet in the ground scene. However, while computer rendering and computational techniques have made significant advances in this area, this complete solution is generally solved with Monte Carlo integration techniques and is still incredibly computationally demanding. It is not yet a practical approach to model scenes of reasonable complexity.

To reduce the computational burden of scene rendering, we decouple the volumetric scattering and absorption from the surface scattering calculations. We first use MODTRAN® to solve the volumetric radiative transfer equations and determine the amount of atmospherically-corrected light that enters our scene from every solid angle in the hemisphere $H$. The resulting scene-radiance calculated for every solid angle is assembled into a faceted sky dome. Each facet in the sky dome is assigned to emit the amount of radiance that enters the scene from that direction. The calculated scene-incident solar irradiance is incorporated into the sky dome either by assigning it to the appropriate facet or by placing it as a point source at the appropriate location on the sky dome. When the modeled sky dome is much larger than the scene, it will accurately model the amount of radiance entering the scene from each direction in the hemisphere. Since this radiance is already atmospherically-corrected, rays cast between the sky dome and our scene model will not experience attenuation. With the lack to participating media to cause attenuation from scattering and absorption, the equation of transfer simplifies to the Light Transport Equation (LTE) \[ \text{LTE} \] 

\[
L(\omega_o; x, \lambda) = L_e(\omega_o; x, \lambda) + \int_{\mathcal{H}(n)} f_r(\omega_o, \omega_i; x, \lambda) L(\omega_i; t(x, \omega_i), \lambda) \cos \theta_i d\omega_i \quad (4.4)
\]

where $L_e(\omega_o; x, \lambda)$ is the radiance emitted by the object at point $x$ and $t(x, \omega_i)$ is a ray casting function. It casts a ray from the point $x$ in the direction $\omega_i$ and returns the first point $x'$ that intersects with that ray. $L(\omega_i; t(x, \omega_i), \lambda)$ is therefore the amount of radiance that originates at point $x'$ and reaches point $x$. Even without the need to calculate volumetric scattering and absorption, solving LTE is still computationally taxing: it requires computing the angle-dependent scattering from the BRDF at each location in the scene and accounting for the visibility relationship between all surfaces. It can be simplified using assumptions already made by our modeling method. First, we assume that all objects in our scene are purely reflective and therefore do not emit radiance. With this assumption, the surface-emitted radiance $L_e = 0$ and the LTE then simplifies to:

\[
L(\omega_o; x, \lambda) = \int_{\mathcal{H}(n)} f_i(\omega_o, \omega_i; x, \lambda) L(\omega_i; t(x, \omega_i), \lambda) \cos \theta_i d\omega_i \quad (4.5)
\]
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This simplified form of the LTE is identical to (2.19) and calculates the total radiance that is reflected by point \( x \) into the observed direction \( \omega_o \). Equation (4.5) can be simplified further by applying the Lambertian assumption. Under this assumption, the reflected radiance is no longer dependent on incident and observation angles and the BRDF \( f_r(\omega_o, \omega_i; x, \lambda) \) simplifies to the diffuse BRDF \( f_{r,d}(x, \lambda) \) and can be removed from the integral:

\[
L(x, \lambda) = f_{r,d}(x, \lambda) \int_{\mathcal{H}(n)} L(t(x, \omega_i), \lambda) \cos \theta_i d\omega_i \quad (4.6)
\]

Under the relation from (2.22), the diffuse BRDF \( f_{r,d} \) is related through the diffuse reflectance \( \rho_d \) by

\[
f_{r,d} = \frac{\rho_d}{\pi}.
\]

Substituting this term into (4.6) and multiplying each side by \( \pi \), we have

\[
\pi L(x, \lambda) = \rho_d(x, \lambda) \int_{\mathcal{H}(n)} L(t(x, \omega_i), \lambda) \cos \theta_i d\omega_i \quad (4.7)
\]

where \( \pi L(x, \lambda) = B(x, \lambda) \) is defined as the radiosity at point \( x \), which is the total power per unit area leaving the surface [5]. Under the Lambertian assumption, we can express (4.7) in terms of the radiosity \( B \) by redefining how the incident radiance is integrated. The integral in (4.7) calculates irradiance incident to a point \( x \) by integrating all incident radiance over the hemisphere \( \mathcal{H} \). Instead, we wish to express this integral in terms of the radiosity incident to \( x \) from all other surfaces in the scene. For two differential surfaces \( dS \) at location \( x \) and \( dS' \) at location \( x' \), geometrically related by Figure 4.2, the radiosity leaving \( dS' \) in the direction \( \theta' \) to the surface \( dS \) is

\[
B(\theta', x', \lambda) = L(x, \lambda) \cos \theta' dS' = \frac{B(x', \lambda) \cos \theta' dS'}{\pi}
\]

(4.8)

Figure 4.2: View factor geometry for two infinitesimal surfaces \( dS \) and \( dS' \) separated by a distance \( r \). The parameter \( \theta \) is defined as the angle made by the connecting line between the surfaces and the surface normal of \( dS \), \( n \). The parameter \( \theta' \) is defined as the angle between that same connecting line and the surface normal of \( dS' \), \( n' \) [5].
where \( \theta' \) is the angle made between the surface normal \( \mathbf{n}' \) of \( dS' \) the line of sight vector between \( dS' \) and \( dS \). The amount of this radiosity that leaves \( dS' \) and reaches \( dS \) is then

\[
B(x, \lambda) = \frac{B(x', \lambda) \cos \theta' \cos \theta dS'dS}{\pi r^2}
\]  

(4.9)

where \( r \) is the distance between the two surfaces and \( \theta \) is the angle made between the surface normal \( \mathbf{n} \) of \( dS \) and the line of sight vector between \( dS' \) and \( dS \). We define the view factor between \( dS' \) and \( dS \), \( F_{dS' \rightarrow dS} \), as the fraction of radiant energy leaving \( dS' \) and falling upon \( dS \) [5]. Under this definition, \( F_{dS' \rightarrow dS} \) is defined as

\[
F_{dS' \rightarrow dS} = \frac{\cos \theta \cos \theta'}{\pi r^2}
\]  

(4.10)

We are now ready to define the radiosity equation, which relates the radiosity leaving a surface to the total radiosity incident to that surface from all other surfaces in the scene:

\[
B(x, \lambda) = \rho_d(x, \lambda) \int_{S' \in M} B(x', \lambda) \frac{F_{dS' \rightarrow dS}}{dS} dS'
\]  

(4.11)

where \( M \) is the set of all surfaces in the scene.

Since our Blender models are composed of discrete facets, (4.11) becomes [8]

\[
B_i(\lambda) = \rho_{d,i}(\lambda) \sum_{j=1}^{N} B_j(\lambda) F_{ij}
\]  

(4.12)

which states that the radiosity \( B_i \) leaving facet \( i \) is the diffuse reflectance of facet \( i \) multiplied by the total radiosity incident to facet \( i \) from all other \( N \) facets in the scene. The view factor \( F_{ij} \) between the two finite surfaces \( i \) and \( j \) is defined as [5]

\[
F_{ij} = \frac{1}{S_i} \int_{S_i} \int_{S_j} \frac{\cos \theta_i \cos \theta_j \text{VIS} dS_i dS_j}{\pi r^2}
\]  

(4.13)

where VIS is an indicator variable that equals 1 if there is a direct line of sight between \( dS_i \) and \( dS_j \) and 0 if there is not.

The radiosity equation requires that each facet in the scene reflects a constant radiosity. This requirement can be managed by making the facets in our Blender scene small. Despite this limitation, the advantage of the radiosity equation is that it models light transport as a system of linear equations. This means it can easily be inverted to solve for diffuse reflectance \( \rho_d \):

\[
\rho_{d,i}(\lambda) = \frac{B_i(\lambda)}{\sum_{j=1}^{N} B_j(\lambda) F_{ij}}
\]  

(4.14)
4.4 Computational Methods

We have developed a MATLAB®-based implementation to solve the forward radiance estimation problem. We will see that this framework can easily be altered to solve the inverse problem of reflectance retrieval. This framework uses our atmospheric models to calculate atmospherically-corrected scene-incident irradiance and at-sensor radiance estimates and uses the form of the LTE to render our Blender models from the point of view of our HSI sensor.

All atmospheric correction is done using the commercially-available program MODTRAN®. MODTRAN® takes as input an atmospheric model that defines the distribution and phase functions of aerosols in the atmosphere. The atmospheric model also defines the number of horizontal layers in a given atmosphere; MODTRAN® models the atmosphere as a series of homogeneous horizontal layers, each with their own aerosol distribution. MODTRAN® uses the atmospheric models created from our measured ASR data and the radiative transfer equations to calculate all atmospherically-compensated quantities required by our model. These quantities are scene-incident diffuse radiance from every solid angle in the hemisphere $H$ above our scene; scene-incident solar irradiance; and the path radiance and atmospheric transmittance parameters $L_p$ and $\tau$ that are required by Equation 2.25 to convert ground-leaving radiance to at-sensor radiance. As described in Section 4.3 the scene-incident diffuse radiance calculated by MODTRAN® is assembled into a faceted sky dome. This sky dome is then projected onto a sky map image for use with our rendering algorithm. Each pixel in this sky map is indexed by azimuth and zenith angle and contains the radiance spectrum incident to the scene from that angle. Since diffuse illumination changes as the sun moves across the sky, one such sky map must be generated for each pass that we fly. Figure 4.3 shows an example of such a sky map. The parameters $L_p$ and $\tau$ determine the diffuse radiance that is scattered into each pixel and the transmittance between the ground to the sensor, respectively. Both of these parameters are a function of sensor altitude and location and must also be generated on a pass-to-pass basis. An example of the calculated transmittance and path radiance are shown in Figure 4.4.

We use the open-source rendering program Mitsuba [25] to render our Blender scenes. With illumination defined by the MODTRAN®-calculated sky map and solar illumination, Mitsuba uses the LTE to calculate the ground-leaving radiance leaving each facet in the given scene. Surface reflections for each material are defined by the ground-truth reflectance factors measured during our data collect. We chose Mitsuba to render our scenes over other rendering software because it provides extensive support for the inclusion of BRDF models, various camera types, and various Monte Carlo integration methods. While we are not yet interested in including BRDF models in our
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Figure 4.3: Sky map for use with our rendering program Mitsuba. Each pixel in the sky map is indexed by azimuth and zenith angle, such that each defines the scene-incident radiance spectra from its given azimuth and zenith angle.

Figure 4.4: Example of (a) atmospheric transmittance $\tau$ and (b) diffuse path radiance $L_p$. 
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rendering, we will show in Chapter 5 that this will eventually be required for accurate modeling. Furthermore, since Mitsuba is open-source, we can verify software performance and make changes as necessary. For example, we have changed the spectral bands over which Mitsuba renders from RGB to match those measured by our HSI sensor. Figure 4.3 shows our primary test site from two vantage points after it has been rendered by Mitsuba. The images have been rendered at different times of day to illustrate how the trees shade on the south side of the building changes over the course of the morning.

Figure 4.5: Our primary test scene as rendered from Mitsuba. The left image is rendered from a nadir-looking camera. The right image is a close up view of the targets on the south side of the building.

For completely accurate at-sensor radiance estimation, we must use Mitsuba to recreate the entire HSI image. This process requires the accurate co-registration between the HSI image and the world coordinate systems, as described in Section 4.2. During rendering, the developed camera model is used to place the rendering camera, originally in world coordinates, at the same location and orientation as the HSI sensor. Once this image has been rendered from the sensor’s point of view, the atmospheric parameters \( L_p \) and \( \tau \) are applied using Equation 2.25 to convert the ground-leaving radiance that Mitsuba estimates to at-sensor radiance. Finally, the HSI sensor’s Point Spread Function (PSF) must be applied to fully recreate the HSI image. The PSF is not strictly required to model our targets since they constitute a large number of unmixed pixels in our HSI images. However, the PSF is necessary for modeling object boundaries and small and sub-pixel targets. Figure 4.6 shows a Mitsuba rendering of our secondary test site from the point of view of our HSI sensor after a PSF has been applied.
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We interface with Mitsuba directly through MATLAB® using RenderToolbox [26]. With RenderToolbox, we can import our Blender models, MODTRAN®-generated sky maps, and manipulate Mitsuba camera locations and rendering parameters from within MATLAB®. In this way, we are able to easily apply our [HSI] camera model to the Mitsuba camera and alter rendering parameters such as image size, camera focal length, and the camera PSF. This provides a simple framework for rendering the images shown in Figures 4.5 and 4.6.

4.5 Model Verification

Mitsuba can successfully render our scenes from the point of view of our [HSI] sensor. However, this does not guarantee its radiometric accuracy. In order to verify that our model produces accurate ground-leaving radiance estimates, we have compared the Mitsuba output for simple, completely Lambertian scenes against that of MODTRAN® and an independently implemented radiosity solver. This radiosity solver solves the radiosity equations to produce ground-leaving radiance over a given scene. Comparing the Mitsuba output with that of MODTRAN® allows us to determine the accuracy of our generated sky maps and how Mitsuba uses them to illuminate our
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Figure 4.7: Ground-leaving radiance comparison between Mitsuba and MODTRAN® for a 100% reflective Lambertian target placed in an open area.

As radiative transfer software, MODTRAN® is capable of computing the ground-leaving radiance for targets under open illumination conditions. We implemented a simple scene in which a single 100% reflective Lambertian target sits in an open area. If our sky map has been generated properly, the MODTRAN®-estimated radiance for this target should match that of Mitsuba. Figure 4.7 shows the comparison between the MODTRAN® and Mitsuba ground-leaving radiance for this target. Since we observe excellent agreement between the two rendering methods, we are confident that our sky maps are accurately generated and that Mitsuba uses them to accurately illuminate our scene.

Next, we compare the results of our radiosity solver with that of Mitsuba for the shaded and sunlit red targets in our primary test scene. Figure 4.8 shows these comparisons for NW1 and NW3 and Figure 4.9 shows these comparisons for SR1 and SR3. We see overall good agreement between Mitsuba and radiosity for all of these targets. We believe that the small visible differences can be attributed to the small computational errors in the radiosity view factor calculation and small geometry errors caused by the Blender-import script. However, the overall agreement confirms that Mitsuba behaves as expected in this case. We next compare the Mitsuba and radiosity ground-leaving radiance results for two white targets in a simple urban canyon; one shaded and one sunlit. Figure 4.10a shows the Mitsuba rendering of this simple urban canyon. The shaded target receives the majority of its
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Figure 4.8: Comparisons between Mitsuba and radiosity ground-leaving radiance estimates for NW1 and NW3.

...illumination from indirectly from the sunlit wall. Because of this indirect illumination modeling, shaded targets in urban canyons are stressing cases for our rendering methods. Figure 4.10b shows the estimated radiance comparison between the estimated Mitsuba and radiance for the shaded target and Figure 4.10c shows the same comparison for the sunlit target. We see good agreement between Mitsuba and radiosity for both targets, therefore validating our use of Mitsuba to solve the LTE and estimate ground-leaving radiance for our scenes.

Figure 4.9: Comparisons between Mitsuba and radiosity ground-leaving radiance estimates for SR1 and SR3.
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Figure 4.10: (a) Mitsuba rendering of the simple urban canyon scene used to compare Mitsuba’s performance to that of our radiosity solver. (b) Comparison between the shaded white target radiance estimated by Mitsuba and radiosity. (c) The same comparison for the sunlit white target.
4.6 Summary

In this chapter, we presented our method for solving the forward modeling problem to predict at-sensor radiance as measured by an HSI sensor. This method is defined by three components: our scene geometry model, co-registration between HSI image coordinate and world coordinate systems, and rendering the scene to solve for ground-leaving radiance. While our scene geometry models will ultimately be constructed algorithmically from measured data, we have initially opted to create them by hand using the computer modeling tool Blender. These hand-crafted models have accurate scene geometry and perfect material segmentation. We therefore will not have to worry about geometric errors confounding our radiance estimation results. Co-registration between the coordinates of this ground model and our HSI sensor is accomplished via an HSI camera model, which accurately maps the world and sensor coordinate systems. With these components in place, we have developed a MATLAB®-based simulation to solve the forward model. MODTRAN® calculates scene-incident illumination in the form of an atmospherically-corrected sky map and solar irradiance spectrum. The rendering software Mitsuba then uses this illumination, our scene geometry models, and HSI camera model to render the scene from the perspective of our HSI sensor. This rendering is done by solving the LTE. Finally, the MODTRAN®-calculated atmospheric path radiance and transmittance are used to convert the ground-leaving radiance generated by Mitsuba to at-sensor radiance.

To confirm this model works as expected, we compared our Mitsuba ground-leaving radiance estimates to those generated by MODTRAN® and a radiosity solver. The radiance calculated by both of these methods matched well with our Mitsuba-generated radiance. This confirms that our sky maps have been generated correctly and that Mitsuba solves the LTE as expected. The next step is to evaluate our model performance against our measured ground-truth and at-sensor radiance.
Chapter 5

Radiance Modeling

Radiance modeling is a vital step towards developing our reflectance retrieval methods. While we will never use radiance for target detection, we can make qualitative comparisons between our modeled radiance and our measured ground-truth and at-sensor radiance. From these comparisons, we may validate our ground truth reflectance factor measurements, scene model, modeling assumptions. These assumptions are that targets are Lambertian, objects have non-varying reflectance signatures over their entire surfaces, and trees cast perfect shadows. Radiance modeling additionally facilitates the study of light transport in an urban environment. From this, we can determine the extent that indirect illumination from objects in our scene spectrally influence targets, and how this illumination decreases with distance.

This chapter is split into three topic areas. First, in Section 5.1 we study the irradiance contributions of objects in our scene to our various targets, and how these contributions differ for targets experiencing open, indirect, and obscured illumination. This gives us a foundation for understanding our target radiance estimates and measurements. Next, in Section 5.2 we evaluate our model performance against our ground-leaving radiance measurements. The ground-leaving radiance comparison is the purest test of our rendering method because the estimation of ground-leaving radiance is done under the same illumination conditions in which our reflectance factors were measured. Additionally, it requires one less atmospheric compensation step than that of at-sensor radiance. This allows us to evaluate our model and our reflectance factor measurements. These measured reflectance factors will be most valid for HSI data taken close in time to them. Section 5.3.1 compares our estimated at-sensor radiance with measured at-sensor radiance taken at these ground-truth times. Comparisons between our modeled and measured at-sensor radiance for such data should be comparable to those for our ground-truth data. The third topic covered in this chapter is
model performance analysis. This analysis will indicate areas for improvement. Section 5.3.2 will explore how the Lambertian modeling assumption leads to at-sensor radiance estimation errors and Section 5.3.3 will discuss two additional hypothesized sources of modeling error. Finally, Section 5.4 suggests the next steps that should be taken to improve our model and Section 5.5 summarizes this chapter.

5.1 Irradiance Contributions

Modeling the incident irradiance at each of our targets allows us to study the effects of obscured and indirect illumination in urban environments, as well as the extent to which objects spectrally influence our targets. To measure irradiance, we placed a spherical camera at the center of each target in our primary scene and at various ground locations in our secondary scene. Spherical cameras record incident radiance to the target at all \(4\pi\) steradians and map these readings to an environment map. The environment map rendered for SR3 is shown in Figure 5.1. Like the sky map described in Section 4.3, the radiance incident to the target from each solid angle over the sphere is mapped to a pixel in the environment map. With each half of the environment map representing one hemisphere, the target comprises the entire bottom half of the image. The slight target warping in the image simply indicates that the target is not on level ground.

We can use these environment maps to determine the overall incident irradiance to a target, as well as constituent sources of that irradiance. Total irradiance \(E_i\) is calculated via (2.27), which is repeated here:

\[
E_i(\lambda) = \int_{\mathcal{H}(n)} L_i(\omega, \lambda) \cos \theta_i d\omega_i
\]  

(5.1)

To segment this irradiance by object, Mitsuba additionally renders an object index image. To render this image, a ray is cast outward from the camera at all observed angles. Each pixel is assigned a value according to which object the corresponding ray first intersects. The total irradiance incident to our target from any given object in the scene is therefore (5.1) evaluated over the solid angles in which our target views that object. In this way, we can accurately determine the total irradiance contribution to our target from every object in the scene. Figure 5.2 shows the nomenclature for each of our targets.

We now analyze the irradiance incident to the targets in our primary test scene. The irradiance sources for each target are plotted as an area graph that individually shows the irradiance from each contributing object. The black line at the top is the total irradiance from all sources. As a
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Figure 5.1: The rendered environment map for SR3. Each pixel in the image is mapped to a solid angle; the radiance recorded at that pixel represents the target radiance incident from that solid angle.

Figure 5.2: Nomenclature and layout for targets in our primary (left) and secondary (right) test scenes.

baseline, the irradiance contribution for NR4 is shown in Figure 5.3. Solar irradiance is plotted in yellow and diffuse atmospheric irradiance is plotted in blue. Since NR4 is sunlit, solar irradiance dominates. Diffuse atmospheric irradiance is highest in the visible blue wavelengths, where solar
irradiance is weakest due to ozone absorption. As can be seen from the total irradiance line, this diffuse atmospheric radiance has a noticeable effect on overall irradiance in the visible wavelengths. This contribution tapers to zero in the SWIR wavelengths. At its location in the field, we see that NR4 receives negligible irradiance from the building. It therefore experiences the open illumination expected by traditional reflectance retrieval methods; they should perform well with this target.

Figure 5.3: Area plot for irradiance incident to NR4, separated by object. At its location in the field, it receives negligible irradiance from the building and can therefore be considered to experience open illumination conditions.

To illustrate the illumination patterns experienced by our obscured and indirect illumination targets, we will show irradiance area plots for the three northern and southern red targets. Figure 5.4 shows the irradiance source area plots for our northern red shaded targets. The amount of diffuse atmosphere that reaches our targets increases with position away from the building. We see that diffuse light reflecting off of the building and the building’s windows do slightly irradiate our shaded targets. However due to the lack of direct illumination, these influences are small and diminish quickly with distance. Their irradiance contributions for NR3 are negligible.

Figure 5.5 shows the irradiance source area plots for our southern red sunlit targets. These targets experience indirect illumination from the building; indeed SR1 receives more irradiance from the building than it does from the atmosphere. As with the northern targets, however, this building influence diminishes quickly with distance. SR2 and SR3 both receive noticeably less irradiance from the building than from the atmosphere. This is consistent with the block and replace effect described in Section 2.5: the building will block diffuse atmospheric light from reaching the target, but will replace that light with indirectly reflected sunlight. As distance from the building increases, the
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Figure 5.4: Sources of incident irradiance to NR1, NR2, and NR3.

Figure 5.5: Sources of incident irradiance to SR1, SR2, and SR3.
building will appear smaller to the target and therefore will block less diffuse atmospheric irradiance and contribute less indirectly reflected radiance. The irradiance contribution from the surrounding trees is minimal.

Figure 5.5 shows that indirect building illumination varies significantly between SR1 and SR2. Our targets are 3 meters on a side. A logical next question is how does indirect illumination vary over this 3 meter distance? To answer this, we turn to the northern red wall, where a vertical red tarp indirectly illuminates a horizontal white tarp. The red tarp’s reflectance has a red edge at 600nm.

This provides a clear spectral feature to track in our irradiance contribution plots. Figure 5.6 shows the irradiance incident to the white target at 1 meter increments away from the red wall, with the left panel showing the irradiance 0.5 meters from the wall and the right panel showing the irradiance 2.5 meters from the wall. We see that 0.5 meters from the red wall, the wall has a significant impact on incident irradiance. After the red edge at 600nm, the added irradiance from the wall is just over 1/3 that of the sun. At 1.5 meters away from the wall, however, that added radiance drops by roughly half. Moving away one meter more, to be located 2.5 meters from the wall, the wall’s irradiance contribution again roughly halves. This means after moving 2 meters away from the red wall, the wall’s irradiance contribution has dropped roughly 75%. A number of external factors could cause this 50% irradiance loss per meter, such as the red tarp, illumination conditions, and illumination geometry; from this test, we cannot conclude that indirect building illumination will drop by 50% per meter. However, we can conclude that indirect illumination from the buildings in our scenes will also decrease rapidly with distance.

We now transition to our secondary site to estimate the irradiance sources for the white cube. With the white cube against the brown building wall and in the urban canyon created by the yellow and brown buildings, it experiences the most complex illumination conditions of all our targets. Figure 5.7 shows the area plots for our model’s estimated irradiance of the cube’s front face and top face. The front face directly faces the yellow building. We see that it receives irradiance mainly from the atmosphere, but also some irradiance via indirect illumination from the grass and the yellow building. The yellow building provides very little irradiance, which is not surprising; studying the red wall has shown how quickly indirect illumination decreases with distance and the white cube is several meters from the yellow building. The grass provides enough irradiance to create a noticeable spectral signature between 700 and 800nm. As we will see, similar signatures appear in our radiance data, especially for shaded targets. This result suggests that these signatures are from grass reflections. Moving to the cube’s top face, we see that it receives almost no irradiance directly from the yellow building and the grass. Rather, its main source of irradiance, aside from the
atmosphere, is the brown building. Indeed, we see a less prominent vegetation signature between 700 and 800 nm than we saw with the cube’s side face. However, the grass and yellow building are likely still influencing the irradiance incident to the cube’s top face through indirect reflections off of the brown building.

In cases of obscured illumination, our model properly predicts that irradiance incident to shaded targets increases proportionally to distance from the obscuring object. For cases of indirect illumination, our model predicts the expected block and replace effect: sunlit buildings will block diffuse atmospheric light from reach a target while at the same time replacing this light with indirectly reflected sunlight. These results confirm the validity of our Mitsuba rendering results.

Furthermore, the irradiance plots have allowed us to study the extent to which indirect
illumination influences target-incident irradiance. As shown by the red wall plots, the amount of indirect illumination received at a target decreases rapidly with the distance from the source of that indirect illumination. We furthermore saw that indirect illumination from grass imparts a specific spectral signature on target-incident irradiance between 700 and 800nm. These findings provide insight into general illumination trends in our test environments and show that our rendering engine behaves as expected. However, behavior consistent with expected trends does not imply radiometric accuracy. Model accuracy must be determined by evaluating its radiance estimates against our measured ground-truth and HSI data.

5.2 Ground-Leaving Radiance Estimation

Ground-leaving radiance is the immediate data product generated by Mitsuba. It is a function of atmospherically-corrected scene illumination, scene geometry and assigned material properties, and Mitsuba’s rendering algorithm. Comparing our rendered ground-leaving radiance with our ground-truth measurements therefore tests the accuracy of each of these components. Since we built and segmented our ground scene models by hand, we do not consider our scene geometry as a source of potential error during these comparisons. By comparing our estimated ground-leaving radiance to the measured ground-truth radiance, we are therefore evaluating the accuracy of our atmospheric models, sky map generation process, reflectance factor measurements, and Mitsuba’s rendering algorithm. For our radiance estimation analysis, we will examine targets from our primary
We recall from Section 3.2.2 that measured reflectance factors only accurately describe apparent reflectance for the illumination and observation geometries in which they are measured. For this reason, we compute our ground-leaving radiance using nadir-looking cameras and sky maps that were generated to match atmospheric illumination conditions at the time that the ground truth measurements for each target were taken. Figure 5.8 shows the comparison between estimated and measured ground leaving radiance for several of the targets in our measurement scenes. In each plot, 8 ground-truth and 8 estimated measurements are shown; measured ground-truth radiance is plotted in blue while the estimated radiance is plotted in red. Notice that the sunlit targets have greater measurement variance than the shaded targets.

We can make several observations from Figure 5.8. First, the visible discontinuity at 1000nm in the measured ground-leaving radiance is caused by a calibration drift in the ASD. This drift puts error bars on our comparison; we consider our estimated data to match our ground truth if...
any inconsistencies between the two data sets are less than the magnitude of this discontinuity. With this in mind, we see that all of our ground-leaving radiance estimates shown in Figure 5.8 fall within this error margin. This suggests that our model can accurately estimate ground-leaving radiance for both shaded and sunlit targets.

### 5.3 At-Sensor Radiance Estimation

At-sensor radiance estimation is a complete test of our illumination model. Modeling our measured HSI data provides challenges not present in ground-leaving radiance estimation, such as a wide range of illumination and viewing geometries and the additional atmospheric modeling step to convert ground-leaving radiance to at-sensor radiance. So long as we evaluate our estimated at-sensor radiance against pixels in the HSI that entirely contain our target, we do not have to model entire HSI images using the process described in Chapter 4. The Lambertian assumption allows us to model at-sensor radiance simply by applying an atmospheric correction to ground-leaving radiance as rendered in Section 5.2. After Mitsuba calculates ground-leaving radiance $L_r$ at the target, it is then converted to at-sensor radiance $L_{as}$ using (2.25), repeated here

$$L_{as}(\lambda) = \tau(\lambda)L_r(\lambda) + L_p(\lambda) \quad (5.2)$$

where $\tau$ and $L_p$ are the transmittance and path radiance between the ground and the sensor. We calculate these values in MODTRAN® using our atmospheric models for scattering and absorption, and the averaged background reflectance for adjacency. After atmospheric compensation, we can compare our radiance estimates directly with the radiance measured by our HSI sensor. For each comparison, we will compare the radiance spectra from eight pixels in our Mitsuba image with that from eight pixels in our measured HSI image.

In this section, we will evaluate our the accuracy of our model for estimating measured at-sensor radiance. First, Section 5.3.1 will how well the model can estimate HSI data taken closest in time with the ground-truth measurements. In theory, the model should have the most success estimating this data since both the HSI data and reflectance factors using by the model were measured under similar illumination conditions. Second, Section 5.3.2 will examine the accuracy of the Lambertian assumption used in the model by comparing estimated target radiance against radiance measured from various look angles. Lastly, Section 5.3.3 will explore how other modeling assumptions could cause lead to radiance estimation errors.
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5.3.1 Evaluation of Modeled Estimates at Times of Ground-Truth Measurements

We begin analysis of our at-sensor radiance modeling by evaluating our model’s performance against HSI data taken of our targets nearest in time to their respective ground-truth measurements. At these times, our measured reflectance factors which we use to render our targets best describe the target’s apparent reflectance. In theory, our modeling performance for ground-leaving radiance will predict our performance here. Performance deviations could suggest errors due to changes in measurement geometry, inaccurate conversion between ground-leaving and at-sensor radiance, or even sensor measurement biases. Figure 5.9 compares our estimated at-sensor radiance with our measured at-sensor radiance for three targets: shaded white, shaded red, and sunlit white.

The comparisons in Figure 5.9 show that our at-sensor radiance estimates are not as accurate as our ground-leaving radiance estimates. A elevated bias in the visible wavelengths has been introduced into our estimate for the white targets; this bias is most visible in the shaded white tarp.

Figure 5.9: Comparison between estimated (red) and measured (blue) at-sensor radiance for radiance measured most closely in time with the ground truth measurements; (a) shaded white tarp, (b) shaded red tarp, and (c) sunlit white tarp.
target and semi-visible in the sunlit white target. A similar bias in the visible wavelengths in the shaded red target can be seen as well. Because our ground-leaving radiance estimates were accurate in this region, there are two possible explanations for this bias. The first is that we overestimate our path radiance, which has the greatest amplitude in the visible wavelengths. This is unlikely, however, as shown by the shaded red target radiance. The red target is effectively black in the blue-green wavelengths, meaning all radiance (estimated and measured) observed from this target in those wavelengths is from the diffuse path radiance. Here we see that the model slightly understimates the path radiance, meaning an overestimated path radiance not the likely cause of our modeling bias in the visible wavelengths. The second, and more likely, source of bias is from our sensor itself. It is possible that our sensor is less sensitive than expected in the visible wavelengths, therefore causing our model to appear biased in this region.

5.3.2 BRDF Analysis

We chose our targets because of their near-Lambertian properties. We therefore expect measured radiance to be consistent across the varied observation geometries utilized during our data collect, including forward scatter, nadir, and backward scatter viewing angles. Figure 5.10 shows the estimated versus measured radiance for the blue target when measured from two forward scatter angles, nadir, and one backscatter angle. We see that our model accurately estimates the nadir measurement, slightly overestimates the back scatter measurement, and underestimates the forward scatter measurement. The severity of the underestimate in the forward scatter direction increases as forward scatter angle increases.

Figure 5.10 shows that the targets used during our data collection campaign are not Lambertian as advertised. Indeed, the blue target appears to be highly forward scattering. This underscores the importance of including BRDF models for all materials in the scene when estimating target radiance. Our targets, which we expected to be Lambertian, seem to show highly non-Lambertian behavior. This implies that our model will poorly estimate the radiance of materials which we expect to have non-trivial BRDF signatures, such as the stucco on building walls.

5.3.3 Hypothesized Error Sources

In the previous subsection, we showed that the model’s Lambertian assumption does not adequately capture the observed target behavior. Here, we will discuss how two additional modeling assumptions could lead to radiance estimation errors.
Recall from Chapter 4 that each object in the scene is populated with a single reflectance factor. This means that the model assumes that each material has uniform spectral properties throughout. A quick glance at almost any surface suggests that all materials are characterized by a range of spectral signatures. Indeed, all objects in the test environment are spatially varying: grass is greener in some areas of the field and dryer in others, and the road is likely spectrally varying due to non-uniform weathering. This suggests that the single reflectance factor used in the model is inadequate to estimate the radiance reflected by these types of objects.

The second simplifying assumption made by the model is that trees are solid objects which cast perfect shadows. Recall from Chapter 3 that trees were present throughout both target scenes. This assumption implies that the model will underestimate the radiance of targets shaded by trees. Further testing is required to validate this hypothesis.
5.4 Model Refinement

In the previous section, we identified target BRDF as a definite source of modeling error and hypothesized two additional sources of error. These modeling errors are conceptually simple to address. In practice, however, implementing modeling solutions to address them is far more complicated.

We will start with the varying material reflectance signatures. Additional reflectance factor measurements should be taken of every side of every building in the test scenes, as well as from multiple locations along the roads and grassy fields measured during the data collection campaign. The additional building measurements will be straightforward to implement because the Blender models can be segmented by object face; each reflectance factor measurement can be assigned to its corresponding building face. Additional reflectance factor measurements must be collected over multiple grass and road locations which are representative of the radiance variation in our measured data. The challenge here is assigning these multiple background reflectance factors to the correct locations in the target scene model. Where buildings have discrete surfaces, we expect the spectral properties of these background materials to vary randomly. In developing these detailed spectral maps of background objects, care must be taken to record how background objects vary spectrally by location. The scene model must be segmented in the same way to create a spectrally and spatially accurate representation of the background materials. For accurate use within our model, these additional reflectance factor measurements must be taken on a morning that experiences similar atmospheric conditions to the morning of our data collection.

Second, we have hypothesized that the current approach of modeling trees as walls will cause underestimated radiance signatures for targets in tree shade. Since trees are ubiquitous in urban environments, accurate radiance estimation in an urban scene will require accurate radiative transfer modeling through foliage. However, modeling light propagation through foliage is incredibly difficult. It requires knowledge of leaf spectral properties, density, and location, all of which vary between particular trees and time of year. A number of algorithms exist to address this problem. These algorithms commonly parameterize leaf area, orientation, and density. These parameters are then used to estimate scattering and absorption characteristics for a given tree, such that radiative transfer through the tree can be modeled similarly to radiative transfer through the atmosphere. Four commonly used algorithms for radiative transfer through such plant canopies have been determined to yield comparable results [29]. One of these algorithms should be adapted to our target scenes. Due to the complexity of radiative transfer through foliage, complete accuracy should not be expected.
from the incorporation of these models. However, complete accuracy may not be necessary. Any model that can approximate the increased radiance and vegetation spectral features observed in our measured radiance will greatly improve the accuracy of our radiance estimations.

Lastly, we have shown that the Lambertian assumption is not adequate to estimate target radiance over a wide range of measurement angles. Two types of BRDF modeling are required to improve radiance estimation results. Most importantly, the BRDF of our targets must be fully characterized. This characterization is vital for further evaluation of our forward model. Second, we need to characterize the BRDF of the three buildings in our target scenes. Since it is not possible to take complete laboratory BRDF measurements of a building, we must develop a BRDF model that accurately describes these surfaces. In particular, the Oren-Nayar BRDF model is effective at modeling the semi-diffuse properties of the buildings in our scenes. This model is controlled by a single roughness parameter which must be tuned to a particular surface. Once this roughness parameter has been found, we expect the Oren-Nayar model to accurately describe building behavior. These BRDF models can easily be implemented in Mitsuba via existing plugins that are included with the software.

5.5 Summary

Development and analysis of our radiance estimation model has provided valuable insight into model performance, areas of required improvement, and how light propagates throughout urban environments. Through modeling irradiance contributions to targets at various locations throughout our scenes, we have discovered that indirect illumination contributions from buildings decrease rapidly with distance. We have also seen in our modeled irradiance the expected block-and-replace effect that is caused by such indirect illumination.

We first compared our ground-leaving radiance results with our measured ground-truth radiance data. This was the most straightforward test of our model because our estimated data was created with the same illumination conditions under which our reflectance factors were measured. We saw overall excellent agreement between our estimated and measured ground-leaving radiance. This verified the general radiometric accuracy of our modeling solution under idealized conditions. We then transitioned to at-sensor radiance comparisons for HSI data taken closest in time to our ground-truth measurements. Our reflectance factors are most valid for this at-sensor data. Since ground-leaving and at-sensor radiance are linearly related under our model, we expect our at-sensor
CHAPTER 5. RADIANCE MODELING

radiance estimates for this HSI data to be accurate. However, our at-sensor modeling results proved more inconsistent.

Our initial at-sensor radiance comparisons set the foundation for our model performance analysis under non-idealized conditions. We first showed that the Lambertian assumption is not adequate to accurately model target spectral behavior; BRDF measurements and models must be incorporated into the model. Second, we hypothesized two additional sources of possible modeling error: that all materials have uniform spectral properties and that trees behave as solid objects. We proposed techniques for addressing these issues.
Chapter 6

Conclusion and Future Work

Hyperspectral Imaging (HSI) seeks to classify materials and detect targets by measuring scene-leaving radiance over hundreds of contiguous spectral bands. Unfortunately, measured radiance cannot directly be used for spectral exploitation because it can be dramatically altered by environmental conditions external to the target. These environmental effects are removed from the measured radiance spectra during reflectance retrieval. However, this is a highly complex problem whose solution requires making simplifying assumptions about the target and its surrounding environment. One such assumption asserts that the target exists in an open environment. As we have seen, this open-environment assumption causes traditional reflectance retrieval methods to fail in urban scenes, where they cannot predict and compensate for instances of obscured and indirect illumination. This leads to poor spectral exploitation.

In this thesis, we have described a method for reflectance retrieval that does not rely upon the open environment assumption and can therefore be applied to HSI data measured over urban environments. Our major contribution to the problem of urban reflectance retrieval has been the performance analysis of this model. We have:

1. Described our implementation of this method for modeling light propagation through urban scenes, therefore increasing the accuracy of reflectance retrieval.

2. Conducted a complete performance analysis of this method by analyzing the effects of indirect and obscured illumination, estimating our measured ground-truth and HSI radiance, and presenting hypotheses for areas of disagreement.

3. Recommended future work to improve the robustness of our model.
CHAPTER 6. CONCLUSION AND FUTURE WORK

New Approach to Urban Reflectance Retrieval

Urban reflectance retrieval must combine measured HSI radiance with scene geometry information. We have described a method that utilizes this knowledge of localized scene geometry and spectral properties of objects in the scene to model how light propagates throughout an urban environment before finally reaching the target. Similar to traditional reflectance retrieval methods, our solution first solves the radiative transfer equation to provide an atmospherically-corrected scene-incident irradiance distribution. We then use our scene geometry model to provide an illumination correction to this scene-incident irradiance. The resulting target-incident irradiance estimate has been corrected to take into account obscured and indirect illumination conditions. We then use the atmospheric transmittance and path radiance calculated between the ground and the HSI sensor to convert measured at-sensor radiance to target-leaving radiance. Diffuse reflectance can then be retrieved by taking the ratio of this extracted target-leaving radiance to our illumination-corrected target-incident irradiance.

We have developed a MATLAB®-based implementation for this method. The radiative transfer software MODerate resolution atmospheric TRANsmission® (MODTRAN) uses our atmospheric models to perform atmospheric correction for scene-incident radiance and to convert measured at-sensor radiance to ground-leaving radiance. The rendering program Mitsuba then takes our scene geometry model and, using this atmospherically-corrected scene-incident irradiance, solves the Light Transport Equation (LTE) to estimate ground-leaving radiance at every point in the scene. We have proposed a method for registering this scene model to our measured HSI image cube. Once this is done, measured radiance is paired with estimated ground-incident irradiance and reflectance is retrieved for every pixel in the data cube.

Model Performance Analysis

To facilitate the evaluation of our technique, a data collection campaign was conducted over two representative urban scenes. A number of colored near-Lambertian targets were arranged throughout the scenes such that they experienced open, obscured, and indirect illumination conditions. Airborne HSI, LAser Detection And Ranging (LADAR), and panchromatic imagery were collected concurrently with target ground-leaving radiance and reflectance factors.

While we are ultimately interested in the inverse problem of reflectance retrieval, model performance evaluation was done via radiance estimation. This allowed us to evaluate the accuracy of our measured ground-truth reflectance factors, our atmospheric models, and the assumptions
CHAPTER 6. CONCLUSION AND FUTURE WORK

made during our rendering method. We showed that our model was successful at estimating our measured ground-leaving radiance for targets under obscured and indirect illumination conditions. Estimating our measured at-sensor radiance proved more difficult. We hypothesized that observed errors could be attributed to varying material reflectance signatures, varying degrees of tree shading, and target Bidirectional Reflectance Distribution Function (BRDF) effects. We recommended ways to incorporate these scene characteristics into our model.

Future Work

Future work should first address the likely sources of error we found in our model. These error sources are from the varying spectral properties of our background materials, improperly modeled tree shading, and the BRDF characteristics of our targets and the buildings in our scenes. They should be addressed by collecting additional reflectance factor measurements of materials in our scenes; incorporating a tree model into our scene to determine if the resulting change in estimated radiance is consistent with our expectations; and taking BRDF measurements of our targets and incorporating a BRDF model, such as the Oren-Nayar model, to estimate indirect reflections off of buildings.

Second, future work must revise how we generate our scene geometry models. We have analyzed our modeling performance using a perfectly segmented hand-made model of our target scene. While this aided our performance analysis by eliminating confounding modeling errors, hand-made models are not a practical solution for modeling scene geometry. Once the current modeling errors are understood, a method for algorithmic geometry model creation and segmentation using our measured LADAR or panchromatic imagery must be developed. At this point, radiance estimation errors derived from uncertainty in scene geometry should be evaluated in more detail.
Bibliography


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