Monte Carlo Simulations as a Tool to Optimize Target Detection by AUV/ROV Laser Line Scanners

Martin Alejandro Montes
University of South Florida

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Monte Carlo Simulations as a Tool to Optimize Target Detection by AUV/ROV Laser Line Scanners

by

Martín Alejandro Montes

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science College of Marine Science University of South Florida

Major Professor: Kendall Carder, Ph.D. Frank Müller-Karger, Ph.D. Pamela Hallock-Muller, Ph. D.

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Keywords: shallow optically turbid waters, underwater light model, unmanned underwater vehicles

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DEDICATIONS

To my lovely daughter Sophia for providing the strength I need in the most difficult moments…
ACKNOWLEDGEMENTS

I would especially like to thank my advisor Dr. Kendall Carder, one of the sharpest scientists I have ever met, for his guidance, support, and patience. There are many good things I can say about Ken who was not only an excellent professional but also a great person.

I won’t forget Flip (Philips Reinersman), my teacher in Monte Carlo simulations. He was always there to answer my questions and didn’t let me give up.

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Thanks to Ted Van Vleet for his perfect assistance in all academic issues; I have not words for his kindness.

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Monte Carlo simulations as a tool to optimize target detection by AUV/ROV laser line
scanners
Martín Alejandro Montes

ABSTRACT

The widespread use of laser line scanners (LLS) aboard unmanned underwater
vehicles in the last decade has opened a unique window to a series of ecological and
military applications. Variability of underwater light fields and complexity of light
contributions reaching the receiver pose a challenge for target detection of LLS under
different environmental conditions. The interference of photons not originating at the
target (e.g. water path, bottom) can often be minimized (e.g., time-gated systems) but not
excluded. Radiative transfer models were developed to better discriminate noise
components from signal contributions at the receiver for two continuous LLS: Real-time
Ocean Bottom Optical Topographer (ROBOT) and Fluorescence Imaging Laser Line
Scanner (FILLS).

Numerical experiments using forward Monte Carlo methods were designed to
explore the effects of diverse water turbidities and bottom reflectances on ROBOT and
FILLS measurements. Interference due to solar light on LLS target detection was also
examined. Reliability of radiative transfer models was tested against standard models
(Hydrolight) and aquarium measurements. In general a green laser was the best all around
choice to detect targets using both LLS sensors. Based on signal-to-noise (S/N) values,
performance of ROBOT for target detection was greater (two-fold) than FILLS because
of the lower contribution of path photons in ROBOT than FILLS. When ROBOT was
located at 1 m above the target, path radiance contributions (noise) were reduced up to
25-fold in clear waters (0.3 mg m\(^{-3}\)) with respect to turbid waters (5 mg m\(^{-3}\)). Since
ROBOT was more discriminative of bottom reflectance discontinuities (high-contrast
transitions) than FILLS, algorithms are proposed to retrieve contrasting man-made targets
such mines.
1 Introduction

Detection of underwater targets continues to be an area of active scientific interest due to the limitations imposed by the optical medium (e.g., turbidity). Submarine feature detection and recognition are important topics in several disciplines such as ecology (e.g., coral fluorescence), geomorphology (e.g., sediment bed forms), petroleum exploration, submarine communications (e.g., cable companies), and port security (Strand, 1995; Moore et al., 2000; Mazel et al., 2003). Micro-topographic mapping (Carder et al. 2003) is also useful in evaluating benthic habitats.

The use of conventional lighting to image objects in marine systems offers advantages in the field-of-view (FOV) (Table 1.1), multi-spectral content, and ease of implementation, but with a performance cost. Image degradation due to poor performance of underwater optical systems is caused by light attenuation and non-target light contribution (noise). Noise is mainly constituted by photons scattered along the optical path between the light source and the receiver. It has different origins (laser vs sunlight photons) and components (backscattering vs forward scattering), and varies with optical environmental characteristics and sensor geometry (Fig. 1.1).

The challenge with which all under-water imaging systems must cope is to minimize noise to better resolve the target of interest (e.g., man-made objects, coral features). Another important constraint of underwater imagers is light attenuation throughout the optical medium. This effect can often be circumvented by increasing source power and/or changing detector sensitivity. In spite of its relevance, this transfer-radiative problem is out of scope of the present thesis. The widespread use of laser-based imagers in the last decade has allowed a significant improvement on target detection with respect to those optical systems using non-collimated light sources. Laser line scanners (LLSs) may overcome target-signal loss to the sensor since they can concentrate a significant flux of radiant energy in a small spot. Likewise, different LLSs configurations make possible noise-reduction by analyzing
temporal and/or spatial variations of photons target-originated (Fournier et al., 1993; Caimi et al., 1998).

Table 1.1: List of symbols and acronyms.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Explanation</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>FOV</td>
<td>Field-of-view of the optical system receiver</td>
<td></td>
</tr>
<tr>
<td>LLS</td>
<td>Laser Line Scanner</td>
<td></td>
</tr>
<tr>
<td>AVIRIS</td>
<td>Airborne Visible-Infrared Imaging Spectrometer</td>
<td></td>
</tr>
<tr>
<td>Lidar</td>
<td>Light detection and ranging</td>
<td></td>
</tr>
<tr>
<td>UUV</td>
<td>Uninhabited underwater vehicles</td>
<td></td>
</tr>
<tr>
<td>AUV</td>
<td>Autonomous underwater vehicles</td>
<td></td>
</tr>
<tr>
<td>ROV</td>
<td>Remotely operated vehicles</td>
<td></td>
</tr>
<tr>
<td>MC</td>
<td>Monte Carlo model</td>
<td></td>
</tr>
<tr>
<td>ROBOT</td>
<td>Real-time Ocean Bottom Optical Topographer</td>
<td></td>
</tr>
<tr>
<td>FILLS</td>
<td>Fluorescence Imagining Laser Line Scan system</td>
<td></td>
</tr>
<tr>
<td>PMT</td>
<td>Photo-multiplier tube</td>
<td></td>
</tr>
<tr>
<td>UIR</td>
<td>Minimum upper imaging range</td>
<td>m</td>
</tr>
<tr>
<td>LIR</td>
<td>Lower imaging range</td>
<td>m</td>
</tr>
<tr>
<td>LSF</td>
<td>Line-spread function</td>
<td></td>
</tr>
<tr>
<td>IOP</td>
<td>Inherent optical properties</td>
<td></td>
</tr>
<tr>
<td>α</td>
<td>Source-detector angle</td>
<td>rad</td>
</tr>
<tr>
<td>Xdet</td>
<td>Source-detector distance</td>
<td>cm</td>
</tr>
<tr>
<td>β</td>
<td>Receiver field-of-view angle</td>
<td>rad</td>
</tr>
<tr>
<td>φ</td>
<td>Azimuthal photon direction</td>
<td>rad</td>
</tr>
<tr>
<td>θ</td>
<td>Zenith photon direction</td>
<td>rad</td>
</tr>
<tr>
<td>ρ</td>
<td>Bottom reflectance or albedo</td>
<td></td>
</tr>
<tr>
<td>ψ</td>
<td>Deflection angle of photon after collision</td>
<td>rad</td>
</tr>
<tr>
<td>λ</td>
<td>Light wavelength</td>
<td>nm</td>
</tr>
<tr>
<td>Ad</td>
<td>Collector area of receiver</td>
<td>m²</td>
</tr>
</tbody>
</table>
Table 1.1: List of symbols and acronyms (cont.).

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<thead>
<tr>
<th>Symbol</th>
<th>Explanation</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ω</td>
<td>Solid angle</td>
<td>sr</td>
</tr>
<tr>
<td>r</td>
<td>Radius of unit sphere</td>
<td>m</td>
</tr>
<tr>
<td>C</td>
<td>Cloudiness shape factor of cardioidal distribution</td>
<td></td>
</tr>
<tr>
<td>nw</td>
<td>Index of refraction of water</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>Initial number of photons</td>
<td></td>
</tr>
<tr>
<td>Q</td>
<td>Radiant energy</td>
<td>J s⁻¹</td>
</tr>
<tr>
<td>L</td>
<td>Spectral radiance without polarization</td>
<td>W m⁻² sr⁻¹ nm⁻¹</td>
</tr>
<tr>
<td>E_d</td>
<td>Downwelling irradiance</td>
<td>W m⁻²</td>
</tr>
<tr>
<td>E_u</td>
<td>Upwelling irradiance</td>
<td>W m⁻²</td>
</tr>
<tr>
<td>BDRF</td>
<td>Bi-directional reflectance functions</td>
<td></td>
</tr>
<tr>
<td>Qrs</td>
<td>Unit sphere partition or quads</td>
<td></td>
</tr>
<tr>
<td>Ξ_d</td>
<td>Lower unit hemisphere</td>
<td></td>
</tr>
<tr>
<td>Ξ_u</td>
<td>Upper unit hemisphere</td>
<td></td>
</tr>
<tr>
<td>l</td>
<td>Optical path-length</td>
<td>m</td>
</tr>
<tr>
<td>τ</td>
<td>optical thickness</td>
<td>m</td>
</tr>
<tr>
<td>σ</td>
<td>Collision cross section</td>
<td>m²</td>
</tr>
<tr>
<td>pdf</td>
<td>Probability density function</td>
<td></td>
</tr>
<tr>
<td>cdf</td>
<td>Cumulative volume scattering function</td>
<td></td>
</tr>
<tr>
<td>r</td>
<td>Geometrical distance</td>
<td>m</td>
</tr>
<tr>
<td>c</td>
<td>Beam total attenuation coefficient</td>
<td>m⁻¹</td>
</tr>
<tr>
<td>a</td>
<td>Total absorption coefficient</td>
<td>m⁻¹</td>
</tr>
<tr>
<td>a_w</td>
<td>Total water absorption coefficient</td>
<td>m⁻¹</td>
</tr>
<tr>
<td>a_{ph}</td>
<td>Specific absorption coefficient of phytoplankton</td>
<td>m² mg⁻¹</td>
</tr>
<tr>
<td>chl</td>
<td>chlorophyll a concentration</td>
<td>mg m⁻³</td>
</tr>
<tr>
<td>b_w</td>
<td>Water scattering coefficient</td>
<td>m⁻¹</td>
</tr>
<tr>
<td>b</td>
<td>Total scattering coefficient</td>
<td>m⁻¹</td>
</tr>
<tr>
<td>Symbol</td>
<td>Explanation</td>
<td>Units</td>
</tr>
<tr>
<td>--------</td>
<td>-------------</td>
<td>-------</td>
</tr>
<tr>
<td>$b_p$</td>
<td>Particle scattering coefficient</td>
<td>m$^{-1}$</td>
</tr>
<tr>
<td>$b_b$</td>
<td>Backscattering coefficient</td>
<td>m$^{-1}$</td>
</tr>
<tr>
<td>$b_{bp}$</td>
<td>Particle backscattering coefficient</td>
<td>m$^{-1}$</td>
</tr>
<tr>
<td>$\omega_o$</td>
<td>Single-scattering albedo</td>
<td></td>
</tr>
<tr>
<td>VSF</td>
<td>Volume scattering function</td>
<td>sr$^{-1}$ m$^{-1}$</td>
</tr>
<tr>
<td>$f_s$</td>
<td>Fraction of diffuse downwelling irradiance to total downwelling irradiance</td>
<td></td>
</tr>
<tr>
<td>$\omega$</td>
<td>Laser divergence angle</td>
<td>mrad</td>
</tr>
<tr>
<td>$\theta_{cone}$</td>
<td>Angle of the photon trajectory to the center line of FOV</td>
<td>rad</td>
</tr>
<tr>
<td>$\theta_{sun}$</td>
<td>Solar zenith angle</td>
<td>rad</td>
</tr>
<tr>
<td>$\beta_{FF}$</td>
<td>Fournier-Forand phase distribution</td>
<td>sr$^{-1}$</td>
</tr>
<tr>
<td>$n_p$</td>
<td>Real part of particle index of refraction/n$_w$</td>
<td></td>
</tr>
<tr>
<td>$\xi$</td>
<td>Junge hyperbolic particle-size distribution</td>
<td></td>
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Fig. 1.1: Photon contributions to an underwater imager. Laser photons (black arrows), sunlight photons (grey arrows), direct photons (big arrows), diffuse photons (small arrows); $\omega =$ laser divergence angle, $\alpha =$ source-detector angle, $\beta =$ receiver field-of-view angle. Notice that optical media above and below the sea-surface are not homogeneous due to time/space changes on atmospheric conditions and water properties. Clouds, aerosols and underwater turbidity patchiness change light field geometry, light intensities, and radiative components at the sensor. Main noise contributions reaching the optical system receiver are backscattering (small black arrows near the main laser beam) and forward-scattering of bottom-reflected photons (small grey arrows). Water (backscattering) and particles (forward-scattering) are primarily responsible for photon collisions along the optical medium between the target and the receiver.
Other advantages of various LLSs are fine spatial resolution (mm), wider range of bottom types (e.g., patchy) compared to acoustic methods, night measurements (active sensors), 3-D mapping, and retrieval of optical properties of the medium (Wells, 1969; Strand, 1997; Moore and Jaffe, 2002; Carder et al., 2003). The aforementioned capabilities make LLSs suitable to ‘ground truth’ remote sensing products in coastal waters. Remote sensing algorithms for bottom classification, in particular those obtained from airborne sensors (e.g., AVIRIS) (Lee et al., 2001), would also demand in situ validation that could be provided by LLS surveys (Costello, 1994). At present, passive sensors can only retrieve coarse bathymetry (Sandidge and Holyer, 1998), and are expected to be very influenced by contrasting features adjacent to the FOV, such as when the bottom is not flat or has a patchy albedo distribution. In that regard, active sensors such as light detection and ranging (Lidar, Light detection and ranging) devices allow for a greater contrast of bottom characteristics. For instance, EAARL (Wright and Brock, 2002) uses a powerful laser source that allows mapping at relatively high-spatial resolutions (spot circa 15 cm horizontal, and 7 cm vertical) from low-flying aircraft. Even with these advantages, airborne laser measurements also require calibration using finer resolution measurements such as provided by LLSs. The main stream of LLS studies concentrates on applications related with mine detection, coral reef health, wreckage mapping, microbathymetry, and bottom albedo characterization (Strand, 1997; Moore and Jaffe, 2002; Carder et al., 2003).

The technological boom of LLSs is partly explained by the recent proliferation of unmanned underwater vehicles (UUVs) including autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) at several marine science institutions in the United States (e.g., Scripps Institution of Oceanography, Woods Hole Oceanographic Institute, University of South Florida, Monterey Bay Research Institute) (Fig. 1.2). LLSs aboard UUVs have lower cost with respect to other platforms (e.g., ships and manned submersibles), can be positioned near the sea floor to measure distances, and may support other sensors (e.g., fluorometers, transmissometers). UUVs have proven to be effective in relatively shallow waters (<30 m) and can be deployed from relative small boats and managed as AUV arrays (Carder et al., 2001).
Unlike ROVs (Fig. 1.2a), AUVs (Fig. 1.2b) can cover long ranges (60 km) in a relative short time (8 h) with high spatial resolution when near the bottom.

Fig. 1.2: Remotely operated vehicles and autonomous underwater vehicles developed or operated by the University of South Florida. a) ROV, b) AUV.

However, ROVs are, in general, easier to manipulate than AUVs. Although less common, LLSs can also be deployed from alternative underwater platforms such as submarines (e.g., US Navy) and moorings (e.g., Monterey Bay Institute). The use of LLSs aboard UUVs introduces another set of variables related with geometric settings (e.g., source-receiver distance, UUV altitude above the bottom) that must be accounted for to minimize noise reaching the LLS receiver. Although noise of LLS measurements can be reduced, there is no single instrumentation capable of completely discriminating between target and ambient signal (noise) contributions. Solutions are partial (e.g., night surveys, time-gating, changes in source-detector angle, fluorescence, shorter distance to
the target even though footprint is reduced) but not absolute. Noise is determined by water (e.g., water scattering vs absorption), surface (e.g., sun altitude), and bottom (e.g., irregular vs flat areas) variability (Reinersman and Carder, 2004). Notice that ambient signal contribution to the total signal is also influenced by optical configuration of the LLS mounted to the UUV. Theoretically, total noise affecting target detection could be measured if all environmental conditions are known during each LLS survey. This approach would require a super optical system (LLS + various types of sensors) which is impractical and expensive because it must be used in defined field scenarios (e.g., there is an infinite combination of environmental conditions). Another complication is that ‘perfect sensors’ do not exist because optical sensors fail in very turbid waters (e.g., the instrument projects a shadow in very scattering waters) (Gordon and Ding, 1992).

By searching a full solution to quantify noise, why not apply air-water radiative transfer models? Underwater light models have proven to be reliable tools to model arbitrary light fields and are potentially suitable to estimate different signal components arriving at the LLS receiver. One of the most popular numerical techniques among the light models is Monte Carlo (MC). Radiative transfer simulations using MC are consistent with other numerical schemes (e.g., invariant embedding, eigenmatrix methods; Mobley et al., 1993). In atmospheric sciences, MC has been applied to calculate light components (direct vs diffuse contributions) reaching airborne or satellite sensors (Reinersman et al., 1995; Miesch et al., 1999). In marine optics, MC have been mainly applied to study sensor shading effects (Gordon and Ding, 1992; Piskozub, 2004) and bottom influence (albedo, slope) (Mobley and Sundman, 2003; Carder et al. 2003) on total signal at the receiver. Although MC methods can model huge numbers of underwater ‘virtual’ light field scenarios without necessary field measurements (Mobley et al., 1993), there have been no attempts to calculate the target signal and the effect of background medium signals on target identification of underwater laser line scanners using MC techniques.

In the first part of this thesis, basic concepts about LLSs and light propagation are described. Methodological aspects in developing MC models for two types of LLSs and design of numerical experiments are fully explicit in the second part. In the third part, results of MC validations, environmental effects on signal-to-noise values at the LLS
receiver, and LLS case studies are presented. In the fourth part, results on the performance of different types of LLS in various environmental scenarios (e.g., turbid vs clear waters) are discussed, and conclusions are summarized. The main intention of this thesis is to demonstrate how MC models can be used to optimize LLS measurements in water bodies with different light fields and better interpret the target signal arriving at the LLS receiver. Target detection resolution of two kinds of LLS sensors aboard UUVs is compared.

1.1 Classification of laser line scanners

There are basically two kinds of LLS systems: continuous and short-pulse laser sources (Moore and Jaffe, 2002; Mazel et al., 2003) (Fig. 1.3). In general, improvement of image formation at the LLS receiver will depend on how much noise is reduced, and the strength of the power source (greater intensity produces better signal-to-noise).

Fig. 1.3: Classification system for underwater imagers (Jaffe, 1990). a) camera-light close, b) camera-light separated, c) synchronous scan, and d) time gated. Notice the narrower illumination volume of laser-based sources compared to camera FOV (b-d).
Based on attenuation lengths (1/beam attenuation), performance of sensors with high-parallax geometry (source and detector are separated with a certain inclination) can easily double (>4) those obtained with an imaging system with minimum distance between source and receiver (~2) (Fig. 1.3a-b). Better resolution in bi-static systems (source-receiver separated) with respect to conventional imagers is due to the lower influence of backscattered photons (‘veiling glow’) coming from the main laser beam (non-target contribution) into the FOV of the sensor. It is similar to the relatively high view angles of a truck driver viewing the road in a snow storm. Scanning of bi-static optical systems usually involves a single-line projection method (fan-type laser with multiple beams) (Kaltenbacher et al., 2000). Push-broom or synchronous scan systems are also continuous LLS that may have parallax geometry (Fig. 1.3c). In this case, noise due to forward scattered photons after target reflection (‘blur’) can be minimized by making smaller receiver FOV and volume illuminated by laser (one single laser beam) (Mullen et al., 1999). Scanning of synchronous optical systems is based on a single-point method (source and receiver are swept simultaneously perpendicular to the UUV direction). Unlike other imagers, synchronous and Lidar (Fig. 1.3d) LLSs suffer power limitation because more energy must be focused in a smaller area (field-limited systems) to obtain greater S/N values. Noise in Lidar imagery is reduced when the camera system is activated at a precise time depending on the range of interest collecting light that has traveled a fixed delay and is relatively free of backscatter information (Fournier et al., 1993). Range-gated systems such as Lidar can also be designed to classify target photons based on polarization filters (Morgan et al., 1997). According to a broader classification of LLSs, optical systems of Figure 1.3 can be grouped as structured illumination techniques (Bailey et al., 2003). Other methods of target detection using lasers are multiple-line, color-coded, and grating projections (Gilbert, 1999).

1.1.1 Real-time Ocean Bottom Optical Topographer

The Real-time Ocean Bottom Optical Topographer (ROBOT) (Carder et al., 2001, 2003) is a bi-static LLS consisting of a fan-beam source and intensified camera receiver
Fig. 1.4: Real-time Ocean Bottom Optical Topographer. a) Diagram showing optical instrumentation, b) ROBOT components inside an AUV. The laser source is a fan-type, and the receiver is a CCD camera (Charged Coupled Device) with more than one pixel. An acoustic-Doppler sensor is located between the source and the receiver to record UUV speed. Source-receiver distance is adjustable (copyright Kaltenbacher et al., 2000).

The CCD camera is an 8 x 10 mm array of 20 x 30 µm pixels, and the source is a green laser Nad-YAG glass (double) (532 nm) with a power of 0.5 W. FOV along UUV travel direction is 28.4°, FOV across UUV travel direction (y-component) is 36.7°, and \( \omega \) is 1.5 milliradians. The typical resolution of the system is 2 x 2 x 2 cm at 2 knots speed. The laser beam is split along the y-component, and its photons spread over an arc of 45°.

A schematic of the ROBOT scanning system is shown in Figure 1.5. Individual frames (topography lines) are assembled into a 3-D image in real time as the UUV passes over the object. Real measurements of ROBOT are made in 3-D using a laser fan-type system spread across the UUV travel direction, and a 2-D CCD array (Kaltenbacher et al., 2000). A single laser-beam is optically spread into a thin fan beam. Beam coverage is spread in one dimension completely and needs only be swept once in a perpendicular direction to obtain a complete image of the area of interest.
Fig. 1.5: Schematic for ROBOT scanning system. A bi-static camera viewing light from a fan-beam laser reflected off the bottom and objects therein. The pixel with the brightest radiance per image column is saved as a measure of the object albedo, and the position of the pixel provides a measure of the range to the object. The spatial sequence of the columnar points creates the range profile shown as the ‘camera view’, and a temporal sequence of ‘camera views’ from video frames is used to build up 3-D images (after Kaltenbacher et al., 2000).

1.1.2 Fluorescence Imagining Laser Line Scan

The Fluorescence Imagining Laser Line Scan system (FILLS) is a synchronous scan system that uses a laser point (small millimeter-size spot) to illuminate an object, and a receiver with a very narrow (~0.573°) FOV (U.S. Navy, Raytheon Electronic Systems Corps., Strand, 1997) (Fig. 1.6). FILLS has an Argon-Ion laser source at 488 nm and four separate photomultiplier receivers (1-pixel resolution each) at 488 nm: blue (10 nm full width at half maximum spectral resolution), 520 nm: green, 580 nm: orange, 685 nm: red (Fig. 1.6a). FILLS has more interference filters than ROBOT because it may
work with scattering (488 nm) and fluorescence (>488 nm) channels. Each receiver consists of a rotating optical assembly (90° scan lines), a controllable aperture assembly, a photo-multiplier tube (PMT), a preamplifier and signal conditioning electronics, and an analog-to-digital converter. Each of the receivers’ rotating optical assemblies are composed of four-faceted mirrors that can be also fitted with polarization analyzers, which allow various aspects of the reflected light field to be evaluated.

FILLS can also be used create color images using a laser source with a different combination of gases (Argon/Krypton). RGB outputs in red (647 nm), green (515 nm)
and blue (488 nm) can be collected at ranges up to one order of magnitude greater with respect to those obtained with ambient light illumination. The power consumption of the sensor is ~7.5 kW (~8,000X more energy is used compared to ROBOT because of the tiny viewing spot and integration time). FILLS geometry partially compensates for the inefficient parallax (light source and receiver are very close each other, ~25 cm separation) of FILLS measurements. Unlike ROBOT, FILLS also can avoid scattering noise due to the medium by detecting fluorescence (target is detected at longer wavelengths than those used for excitation). Nevertheless, the use of fluorescence provides other light interferences such as sunlight near the surface during daylight hours (Mobley, 1994) and bioluminescence (Widder, 2002) during night surveys. In FILLS, source and receiver are moved concurrently during each scan using a sophisticated mechanical system (Fig. 1.6b). Likewise, image gathering and processing time is more complex in FILLS compared to ROBOT. The smaller source-detector angle in FILLS (~2°) compared to ROBOT (up to 45°) makes FILLS measurements close to the target difficult because the minimum upper imaging range (UIR) is constrained to 15 feet (Fig. 1.7).

![Diagram of FILLS](image)

Fig. 1.7: Topographic constraints of FILLS. UIR = upper imaging range, LIR = lower imaging range, $\alpha$ = source-detector angle.
The upper and lower (14.6 m) imagining range limits are adjusted to bracket the range to the sea floor. At 7 m above the bottom, the area illuminated by the source has a 7 mm diameter, the target seen at the receiver is 25.46 cm, and the swath is circa 10 m (8 m usable). Although ROBOT has a less-limited minimum on the upper imaging range, changes in range affect its scanning width (further from the object the larger the area) in the same way as other multiple-beam LLSs. Also a smaller source-detector angle and the single pixel of FILLS do not allow topographic mapping of the seafloor or bottom objects. Because the signal/noise decreases as the optical path between the detector and the target increases (Fig. 1.8), FILLS must be more sensitive than ROBOT by increasing the power source and using a high-gain receiver (e.g., PMT).

Fig. 1.8: Altitude effects on ROBOT footprint and signal arriving to detector: a) UUVZ = 1 m, b) UUVZ = 5 m. Unlike Xdet, source-detector angles are similar in a) and b). Notice that at greater UUV altitudes above the target more pixels in the far-range are particularly affected by the backscattering component and larger the target seen by the sensor.
However under this configuration, path radiance is also increased. Hence, FILLS can operate farther away from the target when turbidity is low; otherwise fluorescent mode is the only alternative. Farther from the target, FILLS measurements are less prone to sea-bottom impacts due to AUV/ROVs bottom irregularities. In terms of construction and operation, ROBOT is cheaper (~$30,000 US) than FILLS (>1 million US) because of the simplicity of ROBOT manipulation and optical components.

1.2 Artifacts of laser line scanners measurements

In general terms, artifacts of LLS measurements are caused by background light (noise) and topographic effects. The first category was already discussed, and it is related to the influence of non-target photons (sunlight and laser-derived) on total signal generated at the LLS receiver. The second category is connected with distortions of LLS measurements caused by targets with non-uniform reflectance or shape. For optical triangulation systems (e.g., ROBOT), the accuracy of the range data depends on proper interpretation of imaged light reflections (Mundy and Porter, 1987; Buzinski et al., 1992).

The most common approach to locate a point on a laser line scan is to find the ‘center’ of each cross-scan power distribution of reflected light. Relatively simple (e.g., mean, median, peak; Soucy et al., 1990) or complex (e.g., space-time analysis; Kanade et al., 1991) statistical methods are used to define the ‘center’ of the spot illuminated. The first family of statistical measures is currently used in continuous lasers, whilst the second is commonly a tool in short-pulse lasers.

LLS imaging involves projecting a light source in an often-turbid medium. A line spread (LSF) or point spread (PSF) function can be used in describing the spatial distribution of scattered photons in 2 and 3-D, respectively. In general, LSF/PSF are Gaussian-type functions that describe how scattered photons are ordered across a line or over a plane. Maximum signal is expected where the laser spot (main laser beam) hits the target surface and lower photos densities tend to be found toward the edges of the field-of-view of the sensor. Notice that fan-type LLSs (e.g., ROBOT) have more than one laser beam hitting the surface and consequently must deal with multiple LSF/PSFs and ranges. LSF or PSF Shapes change due to surface reflectance discontinuities, non-flat surfaces,
and partial occlusion of light beams (Fig. 1.9). In Figure 1.9, the LLS receiver is treated as one-dimensional orthographic, the illuminant has a Gaussian cross-section, and the laser divergence is zero. By convention, laser beam divergence or width is the distance between the beam center and the e^{-2} point (~13.5%) of the irradiance profile. Notice in Figure 1.9 that estimated ranges could lie outside the limits of the target. One possible strategy for reducing these bottom effects is to decrease the width of the laser beam. However, there is a limit to collimate a Gaussian beam due to diffraction effects (e.g., lobes of Bessel function; Bickel et al., 1985).

![Fig. 1.9: Artifacts of laser line measurements due to bottom irregularities: a) reflectance discontinuity, b) corner, c) shape discontinuity with respect to illumination, d) sensor occlusion (copyright Curless and Levoy, 1995); bottom albedo $\rho_1 > \rho_2$. Shape of line spread function is plotted behind the receiver.](image)
Although not represented in Figure 1.9, FILLS and ROBOT measurements can also be affected by speckle, a random interference pattern (Maul, 1985) that has been found when the target surface is sufficiently rough with respect to the laser wavelength (Baribeau and Rioux, 1991). In general, topographic artifacts are more notorious when the sensing system is 3-D (e.g., ROBOT), and corrections become more sophisticated (e.g., 3-D shading or fanning; Moore et al., 2000).

1.2.1 Adjacent effects

Distortions on target detection not only are present when there are irregularities within the FOV of the sensor but also when those irregularities are outside the FOV but relatively close to it (patch is larger than FOV). In this case, ‘adjacency or edge effects’ are produced when adjacent light scatters into the FOV affecting the image formation (Fig. 1.10). Edge effects have a dual contribution of photons to the sensor (backscattered and forward scattered), and are very pronounced in sloping or albedo patchy bottoms (Mobley and Sundman, 2003).

Studies regarding underwater adjacency effects are recently new compared to those carried out in atmospheric/terrestrial sciences (Reinersman et al., 1995; Miesch et al., 1999), even though the theoretical principles are the same and the case studies comparable (e.g., saw-tooth bottom vs linear dunes, cloud-shadow vs seagrass bed patch) (Reinersman et al., 1998; Miesch et al., 1999; Carder et al., 2003; Mobley and Sundman, 2003).

1.3 Line spread function components: Monte Carlo and other approaches

The analysis of LSF/PSF curves is vital to know the LLS performance and understand the importance of noise contributions to the target signal. At the LLS receiver there are two important photon contributions: reflected direct target and path radiance.
Fig. 1.10: Adjacency effects at the LLS receiver. FOV configuration belongs to ROBOT, patchy bottom is represented with black and white rectangles, a box-like bottom featured is mounted close to the far-range of detected area, ambient and laser light photons (arrows) are simultaneously interacting. Strongest signal is coming from the illuminated spot (grey oval). Additional light contributions from pixels surrounding FOV of receiver are determined by bottom reflectance heterogeneities and topographic distortions.

The first signal component has the maximum probability (LSF/PSF can be seen as a probability density function) and coincided with target center (i.e., spot illuminated by the main laser beam). At both sides of the main peak, noise contribution is expected to be greatest, especially over far-range viewing pixels if source-receiver separation is significant. Therefore, more symmetric LSF/PSF could be obtained in those sensor configurations with minimum parallax. Near-range pixels of the LLS receiver may capture target and path radiance due mainly to multiple-scattering (forward scattered photons before and after bottom reflection). The far-range pixels of FOV are expected to have the most degraded signal because path radiance is the highest. In these pixels,
backscattering (single-scattered photons from the main laser beam) increase path radiance contributions with respect to target counts.

Regarding the probabilistic nature of LSF/PSF functions, probabilistic methods such as MC ray-tracing models arise as a feasible solution to improve target detection by un-mixing noise and target signal contributions reaching the LLS sensor. MC methods can also help to examine the effect of each environmental factor (e.g., cloud coverage, stratification of water optical components) or instrument setting (e.g., UUV depth, source-detector angle) on LLS signal/noise variability. In general, MC solutions are based on radiative transfer equations in conjunction with their boundary conditions (Mobley, 1994). MC can be applied to any water body, even those with changing boundary conditions and inherent optical properties (IOPs) in three spatial dimensions. Although computationally inefficient with respect with other numerical methods (e.g., invariant embedding, eigen-matrix methods) (Mobley, 1994), MC is the unique choice when light fields in 3-D or other high dimensional cases need to be modeled. For instance, invariant embedding methods (e.g., Hydrolight software, Sequoia Scientific Inc.) are quick for solving 1-D radiance transfer equation (Mobley and Sundman, 2001). However, effects of irregular bottoms on light fields are easily treated by using MC approaches (Carder et al., 2003; Mobley and Sundman, 2003). MC methods have been already tested for solving adjacency problems observed in coupled atmospheric/terrestrial problems (Miesch et al., 1999) and involving airborne sensors (e.g., AVIRIS; Reinersman et al., 1995). Adjacency effects derived from this approach are comparable to the background/target signal contributions of the LLS problem exposed in the present study.

As a final comment, it is important to differentiate MC methods from illumination and bi-directional reflectance models. Illumination models do not include light interaction with the medium between the light source and the target (i.e., assume that light travels in vacuum). Moreover, photon interactions are modeled using Markov-chain, random-walk techniques, that imply dependency between collisions with only one branch per event (Jensen, 2001). In bi-directional reflectance models, bi-directional reflectance functions (BDRF) describing surface reflectance for all combinations of incident and reflected angles are used (Mobley et al., 2003; Zaneveld and Boss, 2003). An important limitation of BDRF is that they are specific and must be known (e.g., based on canopy
geometric models) or measured \textit{a priori} (e.g., ooid sand) to proceed with radiative calculations. Both illumination and bi-directional reflectance models can be coupled to MC simulations if radiance transfer throughout the water column is part of the model (Pattanaik and Mudur, 1992; Paringit and Nadaoka, 2001).

1.4 Radiometric entities and boundary interactions

In a general form, spectral radiance (L) without polarization can be defined as:

\[
L = \frac{\text{power}}{[\text{projected area}] [\text{solid angle}] [\text{wavelength interval}]} = \frac{\Delta Q}{\Delta t \Delta A_d \cos \theta \sin \theta d \theta d \phi d \lambda} \quad (\text{W m}^{-2} \text{sr}^{-1} \text{nm}^{-1})
\]

where power is the radiant energy Q in Joules or number of photons (e.g., 1 green photon at 550 nm = 3.6 \times 10^{-19} \text{ J}) arriving at the detector surface per unit of time, \(A_d\) is the effective area of the collector or \(\Delta A\) (full area) projected onto a plane perpendicular to the beam direction (Fig. 1.11).

Fig. 1.11: Diagram of a basic spectrometer. The photons have a specific energy Q and are traveling right to left. Light baffles delimit photon energy from a specific solid angle to a discrete diffuser plate, and after being spectrally filtered, photons are collected over the detector surface (copyright Mobley, 1994).
The solid angle $\Delta\Omega = \sin \theta \ d\theta \ d\Phi$ is a measure of angularity in three dimensions (Fig. 1.12). Values of $\Delta\Omega$ can also be derived from $A/r^2$, where $A$ is an infinitesimal area patch on a spherical surface with a size inversely proportional to the square of the radius of the sphere ($r$). Notice that $L$ varies with location, time, direction, and wavelength and is the primary building block for deriving other radiometric definitions. For instance, spectral downward plane irradiance is expressed as follows:

$$E_d = \int \int L |\cos \theta| \ d\Omega$$  \hspace{1cm} (2) 

Fig. 1.12: Geometry of a solid angle: $r$ is the radius of the unit sphere, $A$ is the projected area patch delimited by the solid angle $\Omega$; $\theta$ increases downward from $0$ to $\pi$ whilst $\Phi$ values augment anti-clockwise from $0$ to $2 \pi$.

The term $\cos \theta$ corrects for the projected collector area normal to the photons heading toward the collector from the source of interest. Partition of the unit sphere into quadrilateral domains or quads implies a directional discretization and consequently a finite number of solid angles (Fig. 1.13). Criteria for quad partitions are determined by
the geometry of the problem (i.e., more resolution is emphasized at those angles where more photons are expected). In some cases, a polar cap (~5°) is used (Mobley, 1994) for natural conditions even though this partition might not be convenient when the sun is positioned at relatively small zenith angles. The partition used in this thesis was consistent with a grid of 180 (θ) by 360 (Φ) bins per unit hemisphere, thus solid angles were not necessarily equal for different quads. Directional resolution is constrained due to computing time and memory space requirements that increase when quad resolution is augmented (e.g., 1 x 10⁴ more computer effort if partition is one order of magnitude greater).

Fig. 1.13: Partitioning of the unit sphere in quads. In this specific example there are 5 θ bands and 10 Φ bands per hemisphere (upper hemisphere = Ξu, lower hemisphere = Ξd). The arrow at the right indicates the direction of upwelling radiance that is leaving through quad Qrs with a solid angle, Ωrs. Notice the polar caps in both hemispheres (Q5) and the order of labeling of quads.

A stream of photons traveling throughout a medium different from a vacuum will undergo attenuation in a stochastic way due to absorption and scattering. Therefore, each photon will have a probability of some collision within an optical path-length interval (l):
where \( p(l) \) is the probability density function (pdf) of collision of any individual photon, and \( \sigma \) is the collision cross section. If the total number of photons (\( N_0 \)) is specified in Equation 3, then we obtain an expression for the whole beam. As \( p \) decreases with the optical path-length, fewer photons remain alive and a higher probability of collision results. A useful way to describe probability of photon extinction with \( l \leq L \) is the cumulative volume scattering function (cdf):

\[
P(l) = \int_0^L p^*(l) \, dl = 1 - e^{-l}
\]

where \( p^* \) is \( p \) normalized by \( N_0 \), and \( P(l) \) varies between 0 and 1. The limits of integration in Equation 4 are bounded between 0 and \( L \) instead \(-\infty \) and \(+\infty \) as required by the method of forced collisions (Marchuk et al., 1980). Given that optical attenuation length \( 1/c \), also known as optical thickness (\( \tau \)) or free path length, is related to geometrical distance \( r = \cos \theta / l/c \), where \( c \) is the beam total attenuation coefficient of the medium and \( r/ \cos \theta \) is also known as path length, a random collision point can be found within the interval \( l + dl \) based on a random number \( R \) generated between 0 and 1 using an uniform pdf:

\[
r = -\cos \theta /c \cdot \ln(1-R)
\]

Once a photon encounters an extinction event, the probability that a photon will be scattered is parameterized with the single-scattering albedo (\( \omega_o \)) that is equivalent to the fraction of \( c \) accounted for by the total scattering coefficient (\( b \)) with respect to \( c \) (\( \omega_o = b/c \)). Although the collision point is randomly assigned, photons entering the water column are not scattered equally in all directions or following an isotropic distribution. Instead, water constituents (water, particles) introduce asymmetries on radial photon trajectories. Scattering functions are commonly applied to describe the redistribution of photons in different directions:
\[ P(\theta, \Phi) = 2\pi \int_{0}^{\frac{2\pi}{2}} \int_{0}^{\frac{\pi}{2}} f^*(\theta, \Phi) \, d\Omega \] (6)

where \( P \) now is a cumulative volume scattering function (cdf), which depends on angles \( \theta \) and \( \Phi \), \( f^* \) is a normalized volume scattering function (phase function = VSF/b) if the interaction happens in the water column, or a normalized bottom albedo function (e.g., Lambertian) if the photons are scattered by the bottom. Again by definition, the integral of Eq. 6 is always equal to 1 and can also be understood as the joint probability due to \( \Phi \) (1/\pi) and \( \theta \) changes. Derivation of \( P(\theta, \Phi) \) is crucial for obtaining random directions by inversion that in some cases cannot be achieved analytically except using numerical methods (e.g., Petzold or Kopelevich VSF; see Mobley 1994).

When a collision occurs in the medium, one way of choosing VSF’s (e.g., Rayleigh or molecular vs Petzold or particulate) is to determine the relative contribution of each type of scattering to \( b \) (\( b_w/b \) vs \( b_p/b \)) such that the sum of VSF relative probabilities is equal to 1. As a final step, a random number between 0 and 1 weighted by the scattering type decides what kind of scattering was present during that event. For \( b_{\text{Rayleigh}}/b = 0.3 \), for example, if \( 0 < p < 0.3 \), then a Rayleigh scattering event occurs; otherwise a Petzold scattering event occurs.

1.5 Research Objectives

The aim of the present study is to characterize the target-background signal contributions using 2-D (3-D photon geometry) Monte Carlo runs under different sunlight conditions, optical waters, bottom types and LLS configurations (ROBOT vs FILLS). The final goal is to provide a simple and optimized framework for inexperienced LLS operators who require measurements under different environmental conditions.

The main objectives in this work are:

1. Determine the effect of different sensor configurations, turbidities, and bottom characteristics on the signal/noise values obtained by a LLS system.
2. Obtain a protocol to calculate optimum LLS parameters based on different environmental conditions.

1.6 Hypotheses

A) Target detection using FILLS is more affected by path radiance than using ROBOT, especially in turbid waters. Small laser source-detector angles of FILLS (<2°) make the signal detection less sensitive because of particle backscattering contributions from photons going into the detector and forward-scatter spread of laser photons. In turbid waters more particles enhance these two contributions.

B) ROBOT can be used over a wider range of distances to the target than FILLS especially in turbid waters. Source-detector angular proximity is an impediment when FILLS needs to be used at relatively short distances from the target (“target is detected in the water”). ROBOT can better adjust to such differences due to the variable source-detector angle. In addition, background noise caused by laser beam divergence is expected to be more significant in FILLS due to larger target-detector ranges required.

C) LLS with wavelengths within the red band (e.g., 620 nm) are less influenced by ambient light than green wavelengths in relative deep waters (>3 m). Water absorption increases toward longer wavelengths and is more significant after 700 nm. Sunlight contribution to red photons in the water column is removed by the surface layer (<5 m) except for a small photon fraction derived from solar-stimulated fluorescence. Therefore only red photons provided by a near-bottom LLS would survive at greater depths. Moreover, a relatively short target range is expected due to water absorption itself.

These hypotheses, if proven, will strengthen the relative value of ROBOT relative to FILLS for many bottom-mapping tasks as it has already been demonstrated that ROBOT is capable of 3-dimensional mapping of topography (e.g Carder et al., 2003).
2 Methods

2.1 Types of Monte Carlo schemes

Selecting the right MC model is largely determined by the specific geometry of the problem (Fig. 2.1).

Fig. 2.1: Examples of Monte Carlo schemes: a) forward approach applied to 2-D geometry, the light source (S) is the sun and the receiver (D) is an infinite plane collecting down-welling photons for $E_d$ calculation; b) backwards approach where photons follow an inverse path from S (detector is now the source of photons) to D (ultimately the sun). For instance, if the solar zenith angle changes then the receiver must be changed in the same way to be consistent with the incident light field geometry. In the backward approach, S can be a point. In both MC cases sunlight is the only source involved and radiometric quantities at depth $-Z$. 
In a forward MC approach, tracking of photon trajectories begins at the source (e.g., laser, sun) (Fig. 2.1a), whilst in a backward MC approach photons are launched from the receiver (Fig. 2.1b). This ‘backwards MC’ approach is possible using the reciprocity principle of Helmholtz (Case, 1957) that allows back-tracing the photon history. Another remarkable difference between these two MC schemes is the way radiometric quantities are calculated. For instance, computation of upwelling irradiance applying forward methods requires that the total weights collected at the detector be normalized by the initial number of photon ($N_0$) entering the system. On the other hand, backwards normalization implies that each photon leaving the surface is weighted by a geometric factor (e.g., $1/(1+2/3C)$) proportional to the angular distribution of the incident radiance of the original problem (Fig. 2.2).

Fig. 2.2: Comparison between forward and backwards Monte Carlo models: a) forward basic tracing, b) backwards tracing, B = sea-surface boundary, $n_w$ = water index of refraction, and $\psi$ is the deflection angle of the photon after suffering a collision. In both cases the detector (D) is a plane. Unlike L1, L2 is an upwelling photon observed at a specific point along the surface boundary.
Backward MC is more computationally efficient than forward MC because the number of photons wasted during each simulation is smaller ($N_0$ is not too large). As the detector size decreases the number of incident photons must be increased to maintain high signal-to-noise ratios in the forward MC approach, and becomes infinite if the receiver is a point. Therefore, backward techniques are more statistically appropriate than forward methods to determine radiometric values at specific points in the space. However when the source is a point, backward MC hold no advantage over forward methods. For this reason, a forward approach was chosen in this thesis to solve LLS problems. Interestingly, backward and forward MC methods can also be combined and coupled with radiance atmospheric models.

2.2 Optimization of photon processing during Monte Carlo simulations

Regarding the probabilistic origin of Monte Carlo models, accuracy of MC radiometric outputs relies on the number of initial photons launched and photon interactions throughout the optical medium. Several modeling solutions are used for variance reduction of estimated radiometric quantities: partial extinction of a photon in each collision, wrapping of photon trajectories in lateral boundaries, and generation of daughter rays (Fig. 2.3) (Marchuk et al., 1980; Kirk, 1981; Reinersman and Carder, 2004). All of these techniques have in common a key statement: ‘save photons as much as possible’ in order to reduce error on final calculations. The accuracy of the estimates is proportional to the square root of the number of photon used in the simulation (Mobley et al., 1993).

Spatial dimensions of the light field modeled can modify uncertainty of estimated radiometric quantities. For instance, radiance transfer computations are more precise in a smaller element of space if optical components of the medium remain constant and initial number of photons is sufficiently large. Reinersman and Carder (2004) studied this problem using a hybrid model that combines radiance transfer equation with an iterative relaxation algorithm (finite-element method). Briefly, the 3-D spatial domain is divided into cubes and planes (boundaries) and solution convergence is tested (light fluxes
between elements is constant) for different $N_o$, grid resolution of planes, and partitions of cubes.

Fig. 2.3: Variance reduction in Monte Carlo simulations. The illustration depicts a 2-D problem (component $y$ extends indefinitely) where the top facet is the surface boundary, the bottom facet corresponds to the bottom boundary. In this case, surface and bottom relief are flat. Elements of the diagram: 1) wrapping of photons leaving the lateral boundaries where the entrance or exit point of an incident ray to the surface is represented with a solid circle. 2) partial attenuation of the photon when it encounters a collision point (solid star) where the original weight in this location is not totally extinct but its weight is reduced by single-scattering albedo or the scattering probability. 3) generation of secondary rays (D) from the main ray (M) where the sphere at the collision point indicates the 3-D directionality of main and daughter rays. After a collision, paths followed by each daughter ray are dictated by the VSF of the medium.
Reinersman and Carder (2004) also highlighted the importance of water components (e.g., the more turbid, the more incident photons are needed) and their temporal dynamic (e.g., more resolution near the sea-surface) as additional factors controlling the ideal minimum resolution to reproduce realistic ambient light fields. The use of finite element meshes applied to MC with complex geometries have also been reported for solving problems related with heat transport (Farmer and Howell, 1994). Likewise, techniques for improving the speed of Monte Carlo programs can be found elsewhere (Maltby and Burns, 1991; Henson et al., 1996).

2.3 Basic steps of a forward-in-time realization

An instructive way of viewing the ray-tracing process for a forward MC is as follows: 1) determine position and direction of photon; 2) determine optical distance to the boundary; 3) find a random collision or event point along that boundary; 4) check if photon is still alive after the collision; 5) assign a new direction for the scattered photon that survived the collision using a phase function; 6) repeat until all photons are analyzed (circa of $1 \times 10^6$ initial photons is a reliable photon-packet size to typically start a simulation).

2.3.1 Ambient light model

A flow chart of a 1-D MC (monte1d_main2.cpp, hereafter MC1D) is shown in Figure 2.4. Since the model is plane-parallel, the water body is infinite in horizontal extent and there are not horizontal variations of IOPs or of boundary conditions. In spite of the one-dimensionality, MC1D photon tracking geometry is 3-D. Further assumptions of the model include linear interactions of light with matter, no internal light sources except the sun, only multiple and elastic scattering (e.g., fluorescence and Raman scattering not allowed), and Lambertian bottom reflection.
Fig. 2.4: Flow chart of Monte Carlo simulation (ambient light). Notice that algorithm is structured with two stacks for main and daughter rays: \( N_0 \) = number of incident photons, \( df \) = fraction of diffuse light, \( H_{bottom} \) = bottom depth.
In short, the Setup routine fixes the initial weight \( W_0 \) of photons to one (sum of the weights is the source power and equal to 1 W m\(^{-2} \)), the total number of photons (1-5 x 10\(^6 \)), the IOPs of the water column including the index of refraction of water, and the number of layers along the vertical (homogeneous vs stratified columns). In the same routine, a Set_counters sub-routine place several receivers into the water and at the boundaries (surface and bottom). The next stage in the MC code (Startup()) is related to light transfer calculations above and across the sea-surface. Atmospheric radiance distribution at the sea-surface for direct (sun) and diffuse (sky) incident photons was parameterized as:

\[
f_s = \frac{E_{od\ (sky)}}{E_{od\ (sky)} + E_{od\ (sun)}}
\]

where \( f_s \) is the fraction of diffuse downwelling irradiance to total downwelling irradiance including those collimated beams coming from the sun \( E_{od\ (sun)} \). The diffuse component in this thesis is treated as a cardioidal distribution (Mobley, 1994), thus axially symmetric incident geometry results (no isotropic fields):

\[
L(\Phi, \theta) = L_o + L_o C \cos \theta_s
\]

where \( L \) is equal to \( L_o \), the radiance of the horizon, when the angle with respect to zenith \( \theta_s \) is equal to 90° \( \cos(\pi/2) = 0 \). Notice that \( C \) accounts for cloudiness conditions and has a value of 2 for overcast skies.

Computation of incident-ray geometry is condensed in three functions: radiance_fill, radiance_search, and surface_calc_dir. The first one makes a 2-D array using cardioidal distribution, cdf values, and their corresponding \( \theta \) values; the second one selects cdf for each diffuse ray based on a random sorting of the cardioidal \( \theta \); and the third one determines directionality of each direct ray. MC1D continues calculating the loss of \( W_0 \) after hitting the air-sea interface due to Fresnel reflection as it is clarified in Figure 2.5. Refracted photons are stored in a main stack that is called every time the
function “Process” detects photon extinction (photon weight smaller than a pre-determined threshold such as $10^{-6}$).

The transmitted portion of $W_o$ ($W_i = 1 - W_o$) is going downward (geometric distance is negative), and it is attenuated by two factors: water optical thickness and absorption at the bottom boundary. The function “Before_Collision” of MC1D determines the optical path attenuation of $W_i$ between the initial position and the boundary ($W_b$). If $W_b$ is greater than the minimum weight to survive ($>10^{-12}$) ($W_{\text{min}}$) the function “Daughter ()” is called.

Fig. 2.5: Ray-tracing diagram of a typical 1-D Monte Carlo simulation: $\rho =$ bottom reflectance, incident weight at the surface ($W_o$), weight after fresnel reflection ($W_i$), weight at the boundary ($W_b$), weight after single-scattering ($W_s$), weight at collision point ($W_c$), collision point (star), optical thickness ($\tau$), $l_b$ and $l_c$ are path lengths, $W_{wr}$ and $W_{br}$ are reflected weights. Recall weights are reduced on average as $c*distance$. 

34
In this case, the photon trajectory is downward and a daughter ray is going to be generated at the bottom boundary. A further weight decrease from $W_b$ to $W_{br}$ due to bottom interaction ($W_{br} = W_b \rho$, $\rho =$ bottom albedo) follows, and if $W_{br}$ is still alive, a daughter ray with bottom flag is originated and stored in a daughter stack. This daughter ray has a new direction obtained from a Lambertian cdf:

$$P_{\text{Lambertian}} = 2 \int_0^{\pi/2} \cos \theta \sin \theta \, d\theta = \sin^2 \theta = \Re_1$$

(9)

Here $\theta$ is calculated from a random number between 0 and 1 ($\Re_1$), and $\Phi$ is computed with a second random number as $2 \pi \Re_2$. Notice that for a Lambertian surface, the radiance is reflected equally into all directions even though the probability of leaving the surface is maximal at $\pi/4$ (solid angle varies inversely with area projected). Every time the function “After_Collision” is called, $W_i$ is reduced to $W_c$ at the collision point ($W_c = W_i - W_b$). Later, single-scattering ($\omega_o = b/c$, $b =$ total scattering coefficient) diminishes $W_c$ to $W_s$ ($W_s = \omega_o W_c$), and a new direction is chosen randomly for $W_s$ depending on the interaction type (water vs particle). The fraction of scattering due to water and particles with respect to $b$ determines whether the ray is going to be deflected according to Rayleigh or Petzold VSFs. The calling of “Before_Collision/After_Collision” continues until $W_s < 10^{-6}$.

The photon weight going to the sea-surface can suffer total (internal reflection) or partial reflection (Fresnel) ($W_{wr}$). In the latter case, part of the main ray leaves the sea surface ($W_w$), and it is counted as water-leaving radiance. The reflected part is rotated ($\theta_r = \pi - \theta$) and stored as another daughter ray with a surface flag if $W_{wr} > W_{\text{min}}$. As described before, $W_c$ of an upwelling ray is later diminished due to water (Rayleigh phase) or particle (Petzold phase) collision, and a new direction is assigned to $W_s$ or future $W_i$. It is important to mention that photons traveling horizontally are slightly deflected ($\pm 1 \times 10^{-12}$ rad) with a random upward or downward direction. In order to perform radiometric
calculations (e.g., irradiance and radiance values) two functions were implemented, “Update_wo ()” and “Update_wb (),” that successively sum \( W_i \) and \( W_b \) to each counter (receiver) distributed along the vertical on their way up or down.

A final comment is connected to 2-D and 3-D ambient light geometries. Although ray-tracing is similar to MC1D, additional complexities come out due to ray position updating in more spatial dimensions. This procedure is done for \( x \) and \( y \) vector components based on polar coordinates:

\[
X_{\text{new}} = r \cos \phi \sin \theta, \quad Y_{\text{new}} = r \sin \phi \sin \theta
\]

Radiometric quantities are calculated for infinite rectangles (2-D) or cubes (3-D), and IOPs may change along \( x \) and \( y \) directions. Geometry of plane receivers (e.g., CCD) also adapts to the spatial dimensionality of the problem (e.g., in \( zx \)-dimensions we have an infinite detector along \( y \)). Sea-surface incident light now arrives at segments (2-D) or pixels (3-D) (collimated beams must be distributed among the number of surface bins), and extra boundaries are required for photons crossing \( Y_{\text{Bmin}} \) and \( Y_{\text{Bmax}} \) if the problem presents three-dimensions.

2.3.2 Laser line scanner model

A computing program derived from a 2-D version of monte1d_main2.cpp (AmbientPetzold2d.cpp) was written to analyze laser photon contributions at the ROBOT and FILLS receivers (hereafter LaserPetzold2d.cpp) (Fig. 2.6). Below are the main modifications of MC1D code to incorporate LLS’s geometries: 1) a Set_Detector() function fixes the receiver parameters; 2) an extra boundary corresponding to the detector plane is amalgamated inside the Calc_boun() and Interaction() routines; 3) photons crossing lateral boundaries are totally absorbed (i.e., boundaries are not periodic in \( \text{Wrapp\_photon2}() \)); 4) photons within the receiver’s FOV may be detected (cone_vision()) and are flagged depending if they are derived from target (Direct_target_to_detector()) or optical medium (water + particles) (Weight_to_detector3()) collisions.
Fig. 2.6: Flow chart of Monte Carlo simulation (laser). The 2-D LLS model simulates a single beam across the x-component. $N_0 =$ number of incident photons, $H_{\text{bottom}} =$ bottom depth, $\rho =$ bottom albedo, $\omega =$ laser divergence angle, $W'$s are photon weights, $L_c$ and $L_b$ are optical path-lengths between the initial point and the collision point, and the initial point and the boundary, respectively.
Unlike AmbientPetzold2d.cpp where the light source is the sun and incident rays (diffuse + direct) are crossing the sea-surface along the x-component boundary, the photons in LaserPetzold2d.cpp are injected from a specific bin along the x-component. Along the y-component, 2-D laser MC models assume an infinite target and receiver. As suggested by Mobley and Sundman (2003), lateral boundaries were set according to the horizontal scale of variation of IOPs (more variability narrower the model window). In general, values of \( c \) ranged between 0.22 and 1.5 m\(^{-1}\), and these turbidities corresponded with attenuation lengths between 0.7 and 5 m. Therefore, a water patch size of six meters was established for all LLS runs. Briefly, LaserPetzold2d.cpp starts launching \( N_0 \) initial photons with an individual weight (\( W_i \)) equal to 1 from a source located at distance \( UUV_z \) (altitude above the bottom of UUV) from the target and a position \( X_i \) along the UUV direction. The photons are deviated randomly from the original light pencil due to the specific laser divergence of each LLS source. In Process2(), initial photons pulled out from the main stack begin interacting with the boundaries (surface, bottom and detector). Photons hitting a non-target bottom are distinguished from those hitting a target-bottom using flags. Moreover, photon collisions within the FOV are selectively flagged from those occurring outside the FOV. Notice that events going to the detector boundary do not produce daughter rays (photons are totally absorbed at the receiver plane). Ordering (20 bins per target length or FOV) and counting of weights reaching the LLS receiver are effectuated with Order_Detector() and Radiance_Detector() routines, respectively. Determination of optical path-length (\( L_b \)) and photon weight at the boundary (\( W_b \)) is complicated by the fact of an additional boundary (the LLS receiver). A similar consideration was also made for calculating the optical path length (\( L_c \)) and photon weight (\( W_c \)) at the collision point. Therefore, Get_layer_limits() and Strato_collision() functions were modified accordingly to include interactions of light with the LLS detector plane. In After_Collision2() function, weights within the detector cone of vision have a forced collision within the water column and Weight_to_detector3() is called if \( W_b \) is greater than a minimum weight. Using law of cosines, the angle of the photon trajectory to the center line of the LLS FOV is computed (\( \theta_{cone} \)). A scattering angle
relative to the LLS receiver is calculated as the difference between the original direction of the ray and $\theta_{\text{cone}}$. Then, $\cos(\text{scattering\_angle})$ is used to obtain the probability distribution function of the corresponding VSF (previously selected using a random number and $b_p/b$). The weight going to detector ($W_d$) is obtained as the product between $W_c$, phase scattering function, and $\Omega$. Values of $\Omega$ are computed using the area of the detector, the detector plane inclination and the distance between the collision point and the center of the receiver. The remaining photon weight not going to the detector ($W_w = W_s - W_d$) continues interacting until it is extinct. When the photon hits the target and the remaining weight after bottom reflection ($W_{rd}$) is above the minimum weight to be absorbed ($W_{\text{min}}$), the function `Direct_target_to_detector3()` is called. Part of $W_{rd}$ is the target weight contribution going to the receiver, and is calculated as the product between $W_{rd}$, probability (phase distribution function) derived from a Lambertian radiance, and $\Omega$. The probability of a target weight going to the LLS receiver will be a function of the angle formed between the vertical and the center of the receiver. Unlike FILLS, this angle can be modified in ROBOT along the UUV direction. The remaining portion of $W_{rd}$ is oriented in a new random direction according to a Lambertian radiance distribution.

Weight forcing (i.e., every time a photon collides with the target or is within the FOV of the LLS receiver) is a popular and useful technique (e.g., Lidar models) because it increases the number of rays reaching the sensor and improves considerably the statistical robustness of Monte Carlo outputs.

2.4 Checking reliability of Monte Carlo simulations

2.4.1 Monte Carlo simulations vs a light standard model (Hydrolight)

In order to verify MC outputs, a series of comparisons were made against the now-standard one-dimensional model Hydrolight 4.2 (Mobley and Sundman, 2001) and MC1D. Hydrolight is a radiative transfer numerical model that computes radiance distributions and derived quantities for natural water bodies. In brief, this model solves the time-independent radiative transfer equation (light fields change in milliseconds) using invariant imbedding methods. Unlike the simplified MC version MC1D,
Hydrolight may simulate elastic scattering and a non-flat surface boundary (e.g., effect of capillary waves). Neither MC1D nor Hydrolight are able to compute light polarization effects. Notice that Hydrolight estimations are more accurate than standard field instrumentation if all input variables and parameters are exact, because it has no measurement error in the numerical data. MC1D performance was tested against Hydrolight for calculation of irradiances above the sea-surface, at the water surface and within the water column. MC1D-Hydrolight estimations of vertical attenuation coefficients of diffuse down-welling \( (K_d) \) and upwelling \( (K_u) \) light were also evaluated:

\[
K_d(\lambda) = -\frac{d \{ \ln[E_d(z)] \}}{dz} \tag{11}
\]
\[
K_u(\lambda) = -\frac{d \{ \ln[E_u(z)] \}}{dz} \tag{12}
\]

where \( E_d \) and \( E_u \) are down-welling and upwelling irradiances and \( dz \) is the depth difference between irradiance measurements (Smith and Baker, 1984). Differences between MC1D and Hydrolight models were compared using log RMS (root mean square) (Carder et al., 2004) differences. The parameters for each MC1D realization were as follows: initial number of surface incident photons = \( 5 \times 10^6 \); \( \lambda = 532 \text{ nm} \), \( C = 0 \), and \( f_s = 21\% \). The Solar zenith angle (\( \theta_{\text{sun}} \)) was 29.5\(^\circ\) and matched incident light conditions corresponding with a water body situated at 27\(^\circ\) latitude, during a typical summer day (31 July), and illuminated at 10 am local standard time at 0 degrees longitude. Specifications of MC1D inherent optical properties were similar to “ABCONST“ version of the Hydrolight sub-model: properties were driven by chlorophyll \( a \) concentrations of 0.3 and 5.0 mg m\(^{-3}\). Notice that particle VSF is implicit in backscattering-to-scattering ratio or backscattering efficiency \( (b_b/b) \) values every time Hydrolight runs are modified. Total absorption \( (a) \) and particle scattering \( (b_p) \) coefficients were derived from Equations 3.27 and 3.4, respectively, of Gordon and Morel (1983) and Mobley (1994). Likewise based on Mobley (1994), water absorption \( (a_w) \) coefficient and specific absorption coefficient of phytoplankton \( (a_{pb}) \), and water scattering coefficient \( (b_w) \) were obtained from Tables 3.7 and 3.8, respectively (from Morel, 1974; Prieur and Sathyendranath, 1981). Optical characteristics of the waters under study are presented in Table 2.1. Bottom reflectance
was 15% for the clear water case and 5% for the turbid case. Since fewer photons are
needed in shallower waters to have enough precision in estimated radiometric quantities,
bottom depth in all MC1D-Hydrolight comparisons was 10 m. Also, relatively shallow
water columns avoided longer computer runs.

Table 2.1: Inherent optical properties of MC validation experiments: \( \lambda = 532 \) nm,
sunlight wavelength, chl = chlorophyll \( a \) concentration (mg m\(^{-3}\)), \( \rho \) = bottom albedo, \( a_w =
0.05172 \) m\(^{-1}\) and \( b_w = 0.0218 \) m\(^{-1}\) are absorption and scattering coefficient of water,
respectively, \( a_{ph}^* = 0.4624 \) m\(^2\) mg\(^{-1}\), specific phytoplankton absorption coefficient, \( w_o =
\) single scattering albedo or total scattering coefficient (\( b \)) to beam attenuation (\( c \)) ratio,
\( b_p/b = \) particle scattering efficiency, \( b_{b}/b = \) backscattering efficiency.

<table>
<thead>
<tr>
<th>chl</th>
<th>( \rho )</th>
<th>( a )</th>
<th>( b )</th>
<th>( c )</th>
<th>( w_o )</th>
<th>( b_p/b )</th>
<th>( b_{b}/b )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.3</td>
<td>0.15</td>
<td>0.0648</td>
<td>0.1470</td>
<td>0.2171</td>
<td>0.6872</td>
<td>0.9854</td>
<td>0.025272</td>
</tr>
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<td>5.0</td>
<td>0.05</td>
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<td>0.8391</td>
<td>1.0058</td>
<td>0.8342</td>
<td>0.9974</td>
<td>0.019376</td>
</tr>
</tbody>
</table>

2.4.2 Monte Carlo simulations vs aquarium measurements

The experimental setup consisted of transmittance laser measurements using
ROBOT across a 0.6-m square aquarium. The aquarium volume was filled with a
solution containing diatomaceous earth. This optical medium, characterized by high-
scattering values (\( c = 1.07 \) m\(^{-1}\)), is ideal to collect true backscattering data (multiple
scattering is dismissed). The laser source (\( \lambda = 532 \) nm) was located perpendicular at 0.5
m from a non-reflective target (paper sheet with almost zero reflectance) and the receiver
was set behind the target and facing the laser beam. MC simulations were designed with
bottom albedo and chl absorption equal to zero, thus water was the principal light
absorber (diatomite particles do not absorb photons), and scattering was produced by
particles and water molecules. LSF curves were generated using photons tallied all over
the target along the x-component. In order to validate MC runs, non-linear regression using fifth-order Gaussian functions were applied to experimental data.

2.5 Simulating target detection in different environments

Detection capability of ROBOT and FILLS measurements in water bodies with different turbidities, particle assemblages, and bottom albedos, spectral variations for different sunlight conditions and LLS settings (distance to the bottom, source-detector angle) were evaluated (Table 2.2).

Table 2.2: Parameters for LLS 2-D simulations: chl = chlorophyll a concentration (mg m\(^{-3}\)), \(\rho\) = bottom albedo, \(\lambda\) = laser wavelength (nm), \(\theta_{\text{sun}}\): zenith angle (\(^{\circ}\)), UUV\(_Z\) = UUV altitude above bottom (m), \(\alpha\) = source-detector angle (\(^{\circ}\)), Xdet = source-detector distance (cm). Notice that laser footprint (mm) is very small compared to receiver FOV (cm). Water column depth was in all cases 10 m.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>ROBOT</th>
<th>FILLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>chl</td>
<td>0.3, 5.0</td>
<td>0.3, 5.0</td>
</tr>
<tr>
<td>(\rho)</td>
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<td>0, 0.05, 0.15,0.30</td>
</tr>
<tr>
<td>(\lambda)</td>
<td>400, 532, 620</td>
<td>400, 532, 620</td>
</tr>
<tr>
<td>(\theta_{\text{sun}})</td>
<td>8.7, 29.5, 68.8</td>
<td>8.7, 29.5, 68.8</td>
</tr>
<tr>
<td>UUV(_Z)</td>
<td>1, 5,7</td>
<td>7</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>20, 30</td>
<td>2</td>
</tr>
<tr>
<td>Laser footprint</td>
<td>1.5, 7.5</td>
<td>7</td>
</tr>
<tr>
<td>Xdet</td>
<td>57, 182</td>
<td>25.4</td>
</tr>
<tr>
<td>FOV</td>
<td>58, 269</td>
<td>26</td>
</tr>
<tr>
<td>Receiver</td>
<td>CCD, 400 x 333 pixels</td>
<td>PMT, 1 wide pixel</td>
</tr>
</tbody>
</table>
For LLS receivers with multiple pixels (ROBOT), S/N values were calculated as target/path radiance using the middle pixel of the target. In one-pixel detectors (FILLS), only one integrated target/path radiance or total/path radiance was computed from the model. Simulations were performed for shallow waters (bottom depth = 10 m) one representing clear offshore water (chl = 0.3 mg m\(^{-3}\)), the other more turbid water (chl = 5 mg m\(^{-3}\)) characteristic of ports and estuaries such as Tampa Bay (Table 2.3).

Table 2.3: Water optical components and spectral windows during 2-D simulations: chl = chlorophyll \(a\) concentration (mg m\(^{-3}\)), \(\lambda\) = laser wavelength (nm), \(a_w\) and \(b_w\) are absorption and scattering coefficients of water (m\(^{-1}\)), respectively, \(a_p\) and \(b_p\) are absorption and scattering coefficients of particles (m\(^{-1}\)), respectively, \(a_{ph}\) \(=\) chlorophyll-specific phytoplankton absorption coefficient (m\(^2\) mg\(^{-1}\)), \(w_o\) = single scattering albedo or ratio of total scattering coefficient \((b)\) to beam attenuation coefficient \((c)\), \(b_p/b\) = particle scattering efficiency (particle/total scattering). The number of initial main photons was 5 million for each run.

<table>
<thead>
<tr>
<th>chl</th>
<th>(\lambda)</th>
<th>(a_w)</th>
<th>(b_w)</th>
<th>(a_p)</th>
<th>(b_p)</th>
<th>(a_{ph})</th>
<th>(c)</th>
<th>(w_o)</th>
<th>(b_p/b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.3</td>
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<td>0.0075</td>
<td>0.052</td>
<td>0.196</td>
<td>0.687</td>
<td>0.273</td>
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<td>0.963</td>
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<tr>
<td></td>
<td>532</td>
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<td>0.0022</td>
<td>0.013</td>
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<td>0.462</td>
<td>0.217</td>
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<tr>
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<tr>
<td></td>
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<td>0.051</td>
<td>0.722</td>
<td>0.276</td>
<td>1.084</td>
<td>0.667</td>
<td>0.998</td>
</tr>
</tbody>
</table>

In relatively clear waters, total light attenuation is largest at \(\lambda = 620\) nm since water itself is the main absorber. The single-scattering albedo is greater at shorter wavelengths (\(\lambda = 400\) nm) where water absorption is the smallest. Conversely, particle scattering efficiency peaks relative to molecular scattering at longer \(\lambda\)'s because of the
smaller molecular scattering values. In relatively turbid waters, total light attenuation is strongest at blue wavelengths and maximum \( w_o \) values are shifted to green \( \lambda \)'s. Similar to low-chl waters, particle scattering efficiency peaks at longest wavelengths.

Bottom reflectance values encompassed a wide range of benthic substrates such as sea-grass beds \( (\rho = 5\%) \) and sandy sediments \( (\rho = 30\%) \). Given the heterogeneity of substrates to be measured during LLS missions, intermediate bottom brightness (mixed end members) values were part of the simulations. A totally absorbing bottom \( (\rho = 0\%) \) was of interest because it allows true path radiance calculation. In nature, this type of bottom is associated with anoxic pool patches.

Since range measurements using LLSs are influenced by bottom reflectance, bottom albedo retrieval algorithms were developed for a real case of bottom albedo discontinuity (coral reef ‘halo’) assuming a flat target. The coral reef ‘halo’ is a band of nearby sand between the base of the reef and the outlying beds of seagrass, and it is mainly formed by echinoid (\( Diadema antillarum \)) grazing activity during nighttime hours (Ogden et al., 1973). Change of ‘halo’ diameter has been attributed to impact due to human activities such over-fishing and introduction of new diseases (Lessios, 1988). For ROBOT, three kinds of S/N indices were proposed to construct LSF-\( \rho \) relationships: 1) \( (W_{\text{max}}-W_{\text{min}})_{\text{NEAR}} \) or signal difference between photons collected at the middle pixel of receiver \( (W_{\text{max}}) \) and in the near range, 2) \( (W_{\text{max}}-W_{\text{min}})_{\text{FAR}} \) or signal difference between photons collected at the middle pixel of receiver and in the far range, and 3) \( W_{\text{max}} \). Regarding the lack of pixels in FILLS (only one-wide pixel is collecting the whole signal at a single instant in time), total signal reaching the detector was analyzed. Linearity of bottom-albedo-retrieval algorithms was also explored by fitting second-order parabolic models.

To study solar altitude effects on LLS signals, three solar zenith angles \( (\theta_{\text{sun}} = 8.7^\circ, 29.5^\circ, 68.8^\circ) \) corresponding to morning, noon and evening conditions of a typical cloud-free day of summer in Tampa Bay were selected. The remaining atmospheric parameters (e.g., \( C, f_s \)) were similar to those proposed for validating MC1D.

The effect of different particle assemblages on S/N values of ROBOT and FILLS receivers was studied considering case studies with variable particle composition (organic
vs inorganic) and size (small vs large). Regarding the relationship between volume scattering functions and particle optical characteristics, a specific VSF (Fournier-Forand), which depends on the real part of index of refraction (n_p) and the slope of the Junge hyperbolic particle-size distribution (ξ), was selected from the literature (Fournier and Forand, 1994). Fournier-Forand phase function (β_{FF}) is (Fournier and Jonasz, 1999):

\[
\beta_{FF}(\psi) = \frac{1}{4\pi(1-\delta_v^2)} [v(1-\delta)(1-\delta_v^\gamma) + [\delta(1-\delta_v^\gamma) - v(1-\delta) \sin^2(\psi/2)] + [(1-\delta_v^{180})/(16\pi(\delta_{180}-1)\delta_v^{180})] (3 \cos^2\psi-1) \]

(13)

where \( v = (3-\xi)/2, \delta = [4/(3(n_p-1)^2)] \sin^2(\psi/2) \)

(14)

Recall that \( \xi \) is the linear slope of the hyperbolic cumulative distribution function in log-log space (Junge, 1955). By integrating (11) over 2\( \pi \) steradians in the backward direction, the particle backscattering efficiency can be obtained:

\[
\tilde{b}_{bp} = (1-\delta_{90}^{\psi+1} - 0.5 (1-\delta_{90}^{\psi}))/((1-\delta_{90})\delta_{90}^{\psi})
\]

(15)

\( \delta_{90} \) and \( \delta_{180} \) are \( \delta \) evaluated at the scattering angle \( \psi = 90^\circ \) and \( \psi = 180^\circ \), respectively.

Caution is advised in applying this model in areas where phytoplankton or detritus are strong light absorbers because the imaginary part of the index of refraction (absorption) starts having a significant effect on VSF (> 5% error, Twardoswki et al., 2001) and has been ignored. Likewise, deviations of the \( \xi \) model can be expected if biology dominates physics (turbulence) in term of changing the slope of bulk particle-size distribution (non-Jungian slopes, e.g., red-tide phytoplankton blooms, an abundant swarm of calanoid copepods). Notice that each value of the index of refraction \( m = n_p + i n_p' \) is also composed of an imaginary part \( n_p' \) related to absorption characteristics of particles.
Values of $n_p$ can be derived using Van de Hulst simplifications of Mie theory for non-absorbing spheres (Van de Hulst, 1946) which require knowledge about scattering efficiencies, particle cross sectional areas, and number of particles (Carder et al., 1972).

Values of $\xi$ can be obtained from particle-size distributions in the ocean:

$$N(D) = N_o (D/D_o)^{-\xi}$$

(16)

where $N(D)$ is the number of particles per unit of volume per unit of size bin ($D$), $N_o$ is the density of particles at $D_o$ or a reference particle diameter (e.g. 1 micron).

For the purpose of LLS simulations, four cases studies of particle assemblages were investigated: TYPE I = medium-size-organic ($n_p = 1.02$, $\xi = 3.6$), TYPE II = medium-size-inorganic ($n_p = 1.26$, $\xi = 3.6$), TYPE III = large-size-mixed-composition ($n_p = 1.10$, $\xi = 3.1$), and TYPE IV = small-size-mixed-composition ($n_p = 1.10$, $\xi = 4.0$). For hyperbolic slopes $\xi$ less or equal to 3.6, $\tilde{h}_{bp}$ values are approximately independent of $\xi$ (Twardoswki et al., 2001). Therefore, $n_p$ values are expected to have a significant effect on TYPE I and TYPE II assemblages due to changes in $\tilde{h}_{bp}$. A constant $n_p$, which is similar to that estimated for a Petzold VSF, was used to evaluate the effect of particle-size changes on $\beta_{FF}$ ($\psi$), and consequently in LSF’s formed at the FILLS and ROBOT receivers. In order to minimize absorption effects and maximize S/N, a bright bottom ($\rho = 0.3$), low water turbidity (chl: 0.3 mg m$^{-3}$), and a green laser (532 nm) were chosen for all numerical experiments. The use of a green laser is also particularly advantageous to reduce changes on $n_p$ due to absorbing pigments. To make ROBOT less influenced by bottom-reflected photons and more sensitive to variations in light distribution along the optical path between the receiver and target, an altitude above the bottom of 5 m was set instead of 1 m. Considering a light field structured according to a FF VSF, random scattering directions were generated by constructing a cumulative volume scattering distribution function based on Equations 11, 12 and 13. Hence, the new cdf and pdf corresponding to Fournier-Forand VSF were inserted in After_collision2() and
Weight_to_detector3() functions of modified LaserPetzold2.cpp (see Fig. 2.6). Examples of different $\beta_{FF}$’s and cdf’s for particles with different indices of refraction (real part) and size distribution are shown in Figure 2.7.

![Graph](image)

**Fig. 2.7:** Fournier-Forand scattering functions: a) Particle phase function, b) Cumulative volume scattering function of VSF for particles with different indices of refraction ($n_p$, real part) and Junge slopes ($\xi$) as a function of the scattering angle. TYPE I = medium-size-organic ($n_p = 1.02$, $\xi = 3.6$, dotted line), TYPE II = medium-size-inorganic ($n_p = 1.26$, $\xi = 3.6$, solid line), TYPE III = large-size-mixed-composition ($n_p = 1.10$, $\xi = 3.1$, dash line), TYPE IV = small-size-mixed-composition ($n_p = 1.10$, $\xi = 4.0$, dash-dot line).
Type I and TYPE III populations have a more important forward-scattering lobe than populations II and III due to their larger size or lower refractive index (Fig. 2.7a). On the other hand, TYPE II and IV were curves that presented a significant fraction of backscattering relative to the total scattering. Indeed, these cases corresponded with very small particles or with particles characterized by the largest index of refraction.

Based on their cumulative volume scattering functions, 50% of total scattering was concentrated between 0.06 (TYPE III) and 0.5° (TYPE IV) (Fig. 2.7b). Values of $\tilde{b}_{bp}$ for each kind of particle population were: $2.479 \times 10^{-3}$ (TYPE I), $5.568 \times 10^{-3}$ (TYPE II), $1.779 \times 10^{-3}$ (TYPE III), $5.45 \times 10^{-2}$ (TYPE IV). A practical application of target detection in waters with variable resuspension and particle composition is presented in the results. For ROBOT, only those runs with $UUV_Z = 7$ m were analyzed to enhance the effect of water constituents and minimize bottom effects on LSF formed at the receiver.

To make more comparable environmental effects on target detection performance between LLSs, numerical experiments were also performed using a hypothetical FILLS receiver with multiple pixels. Likewise, to avoid S/N differences caused by dissimilar $UUV_Z$ ranges, additional ROBOT runs were initialized with an altitude above bottom of 7 m. Notice that the area seen by an LLS detector (FOV) is variable in ROBOT with respect to FILLS because source-detector and distance above the target are constant in FILLS.

2.6 Software design, implementation and machine performance

During MC1D development, code structure was optimized using templates derived from C++ Standard Template Library. For instance, daughter rays generated through ray-tracing were manipulated using stack templates already specified in stack.h. Code re-use and encapsulation (classes) are among the most popular programming techniques to make time-efficient algorithms in a more compact way. Introduction of pointers as input arguments of functions was minimized to avoid system stability.
problems during simulations. Some examples of MC1D performance based on simulation times obtained with a Pentium 4 machine (2.8 Ghz, Dell inc.) are shown in Table 2.4.

In general, longer runs were those with relatively highly reflective bottoms, shallow water columns, low chl values, and characterized by a larger number of daughter rays. Increase of water column structure was also among those factors affecting negatively on computing efficiency in each realization. This effect is variable depending on the number of layers along the vertical and their relative turbidity. The C++ Linux environment used for MC1D simulations did not have a graphic interface, and the output was visualized using high-level languages such Matlab. It is intended in the near future to write new MC distributions based on Borland C++, TKC or PDL (Perl). Likewise, parallel-programming methods (Message Passing Interface, MPI) will be implemented to speed up every run in more time-consuming runs (e.g., 3-D light models with irregular bathymetry).

Table 2.4: Monte Carlo algorithm efficiency under different initial settings: chl = chlorophyll $a$ concentration (mg m$^{-3}$), Hbottom = bottom depth (m), $\rho$ = bottom albedo, $N_{DAU}$ = number of daughter rays resulting at the end of the run (interactions) $10^3$, $T_{RUN}$ = simulation running time (min); $N_o = 1 \times 10^4$ photons, $f_s = 0.21$, $\theta_{sun} = 29.5^\circ$, and $\Phi_{sun} = 0^\circ$.

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<th>$T_{RUN}$ (secs)</th>
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3 Results

3.1 Validation of Monte Carlo simulations

Comparisons between MC1D and Hydrolight irradiance outputs for a water column of 10 m, \( N_0 = 5 \times 10^6 \) photons and an incident irradiance of 1 W m\(^{-2}\) are presented in Figure 3.1.

![Figure 3.1](image)

Fig. 3.1: Validation of Monte Carlo simulations against Hydrolight. Downwelling \( (E_d) \) and upwelling \( (E_u) \) irradiances are plotted as a function of depth \( (Z) \). a) and c) chl = 0.3 mg m\(^{-3}\), b) and d) chl = 5 mg m\(^{-3}\), MC1D (solid circles), Hydrolight (empty circles).
Notice the increase of upwelling photons with depth in clear \((\rho = 0.15)\) with respect to turbid \((\rho = 0.05)\) waters. At low water turbidities \((\text{chl} = 0.3 \text{ mg m}^{-3})\), the proportion of photons above the sea surface (water leaving + fresnel reflected photons) was quite similar \(< 1\% \text{ difference}\) in MC1D \((\Eu_{u0+} = 0.0529 \text{ W m}^{-2})\) and Hydrolight \((\Eu_{u0+} = 0.0536 \text{ W m}^{-2})\) models. In turbid waters \((\text{chl} = 5 \text{ mg m}^{-3})\), the relative difference was circa 2.5\% \((\text{MC1D } \Eu_{u0+} = 0.0470 \text{ W m}^{-2}, \text{Hydrolight } \Eu_{u0+} = 0.0482 \text{ W m}^{-2})\).

Simulations in clear water for \(E_d\) and \(E_u\) showed a difference between MC1D and Hydrolight of 1.04 and 1.31\% RMSlog, respectively. Maximum error was found near the bottom for both radiometric estimates (up to 2\%).

Differences of \(E_d\) and \(E_u\) between MC1D and Hydrolight models were examined using one random ‘seed’, thus irradiance computations are expected to have the largest error compared with those estimates based on statistics of many runs. In general, correspondence between MC1D and Hydrolight for \(E_d\) and \(E_u\) values was poorer in more turbid waters \((\text{chl} = 5 \text{ mg m}^{-3})\). Error in upwelling irradiances \((\text{RMSlog} \sim 4.04\%)\) was greater than computed for downwelling irradiances \((\text{RMSlog} \sim 2.86\%)\). In both \(E_d\) and \(E_u\) estimations, larger differences were obtained with depth \((\sim 5\%)\). Agreement between MC1D and Hydrolight estimates of vertical attenuation coefficients was also very remarkable. Differences in \(K_d\) for clear waters \((\sim 1.1\%)\) were smaller than those for turbid waters \((\sim 1.4\%)\). However, \(K_u\) values of MC1D were closer to \(K_u\) values of Hydrolight in turbid waters \((\sim 2.2\%)\) compared to clear waters \((\sim 5.6\%)\).

Reliability of MC1D to estimate a radiometric quantity was also confirmed when MC1D and aquarium measurements of ROBOT line spread function were compared (Fig. 3.2). The greatest differences between experimental and modeled transmitted data were observed near the middle pixel \((\sim 0-3 \text{ cm})\). A fifth-order Gaussian in each kind of data evidenced a more important radial spreading of photons (coefficient B in Table 3.1) in the LSF generated with aquarium measurements. This is to be expected since \(n_p\) for diatomaceous earth (silica frustules in aquarium) were higher than modeled values using the average Petzold phase function of Mobley (1994).
3.2 Effect of different water turbidities

The variation of total signal and signal contributions in FILLS and ROBOT receivers are represented in Figures 3.3 to 3.5.

![Validation of Monte Carlo simulations against aquarium measurements](image)

**Fig. 3.2**: Validation of Monte Carlo simulations against aquarium measurements. Aquarium measurements (empty circles) vs Monte Carlo simulations (LaserPetzold2d.cpp). Only data 10 cm away (area seen by the receiver is 33 cm) from the target center is plotted to emphasize those points with the largest variability.

**Table 3.1**: Curve fitting of true path radiance of modeled vs aquarium measurements. The statistical Gaussian model is: $Y = Y_0 + A \exp^{(-0.5 \times \text{abs}(X-X_0)/B)^C}$, where $X$ is the distance from the target center $X_0$ and $Y$ is the estimated number of photons reaching $X$ bin and normalized to the target middle pixel.

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
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<td>0.0091</td>
</tr>
<tr>
<td>A</td>
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<td>0.989</td>
</tr>
<tr>
<td>B</td>
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<td>0.0041</td>
</tr>
<tr>
<td>C</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>XO</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Fig. 3.3: Effect of water turbidity on FILLS performance: a) Hypothetical LSF for path radiance (solid triangles) and target contributions (empty triangles) in clear waters (left axis). Total path radiance (solid line) and target (dotted line) integrated weights in one pixel (right axis), b) Total signal in clear (solid circles) and turbid (empty circles) waters (left axis). Total integrated weights in one pixel in clear (solid line) and turbid (dotted line) waters (right axis). Distance to the target = 7 m, $\rho = 0.3$, and $\lambda = 532$ nm.

For FILLS, the path radiance contribution in clear waters was circa eight times larger than target contribution (Fig. 3.3a, right axis). Path radiance is enhanced in the far-range of the FOV and was manifested as a bulge in the LSF shape (Fig. 3.3a, left axis). At high turbidities ($c \sim 1$), the total signal reaching the receiver suffered a drastic flattening (Fig. 3.3b, left axis). In Figure 3.3b (right axis), total weights collected within
one pixel of FILLS’ receiver (~25 cm) in low-chl waters were more than 400 times
greater than those tallied in turbid waters (optical depth is reduced five-fold). Not
surprising, path radiance in turbid waters represented a larger fraction (99%) of total
signal with respect to that calculated for clear waters (89%). In Figure 3.4 is depicted the
influence of turbidity on LSF of the ROBOT sensor at two altitudes above the target. Not
surprisingly, performance based on S/N values was overwhelmingly superior in ROBOT
(clear waters, S/N = 253.4) with respect to FILLS (S/N<1).

Fig. 3.4: Effect of water turbidity on ROBOT performance. UUVZ = 1 m, α = 30° and
Xdet = 182 cm. a) path radiance (solid triangles) and target contributions (empty
triangles) in clear waters. b) total signal in clear (solid circles) and turbid (empty circles)
waters. Panels c) and d) idem as a) and b) but UUVZ = 5 m, α = 20° and Xdet = 57 cm.
For all runs, ρ = 0.3 and λ = 532 nm. Notice that total signal in turbid waters is negligible
(S/N<1) when ROBOT altitude is 5 m above the target.
Part of this difference was caused by UUVZ differences between FILLs and ROBOT. Therefore, an additional set of runs with ROBOT at 7 m above the bottom was carried out and still supported a better target detection using a bi-static configuration (S/N ROBOT \approx 2*S/N hypothetic FILLs) instead of a synchronous optical system (data not illustrated). In turbid waters, image quality generated by ROBOT was degraded with respect to clear waters but signal-to-noise was above 1 (S/N = 13.4).

In spite of the larger interaction between the laser beam and the bottom at UUVZ = 1 m (Fig. 3.4a-b), path radiance contribution was a minor term with respect to the target photons. This fact emphasizes the superiority of a bi-static optical arrangement for target detection compared with FILLs. Path radiance in ROBOT at 1 m altitude accounted for a smaller fraction in the middle pixel observed by the receiver. However, non-target contribution dominates the signal observed to the left of the peak (Fig. 3.4a). As expected, a larger FOV in ROBOT with respect to FILLs (ROBOT has a much smaller FOV per pixel than FILLs, which has only one large pixel), integrated path radiance along the target radius was larger in ROBOT. Nevertheless in ROBOT, path radiance per single pixel was insignificant to the right of the laser beam. This value can be subtracted from the peak-value pixel to provide a measure of the target radiance. Note that integrating the forward-scattered radiance (multiple-scattering component of path radiance) with the peak radiance for the right side provides a first estimate of half the target brightness if corrections for path attenuation (−a + b \cdot X, where X is side scattering beyond the FOV and may be 2 or 3).

In turbid waters, target-originated weights were more homogenously distributed over the FOV of ROBOT (Fig. 3.4b). This broader pattern of LSF was also connected with less total signal at the receiver compared with simulations in clear waters due to path radiance increase with turbidity. In general terms, as the target contribution dominates total signal in clear waters, path radiance contribution does in turbid waters.

As ROBOT altitude above the target increases five-fold, detection capability in clear waters decreases 45 times (S/N = 5.6) (Fig. 3.4c) and the target is no longer seen in turbid waters (Fig. 3.4d). Likewise, path radiance contribution increases at longer distances from the bottom and modifies greatly the basic Gaussian shape of LSF (asymmetry more
evident in the far-range). Up to five times the loss in total signal was calculated when ROBOT has a UUVz of 5 m and source-detector angle of 20° (Fig. 3.4b, d).

3.3 Effect of different bottom albedos

LSF’s for path radiance and total signal are modeled for FILLS and ROBOT in Figure 3.5 and Figure 3.6 as a function of bottom reflectance variations.

Fig. 3.5: Effect of bottom albedo on FILLS performance: a) path radiance of hypothetical multiple-pixel sensor (left axis), $\rho = 0.05$ (solid rectangles), $\rho = 0.15$ (solid circles), and $\rho = 0.30$ (solid triangles), integrated weights over one wide pixel (right axis) are indicated with a constant value for $\rho = 0.05$ (dotted line), $\rho = 0.15$ (thin solid line), and $\rho = 0.30$ (thick solid line). b) total signal, $\rho = 0.05$ (empty rectangles), $\rho = 0.15$ (empty circles), and $\rho = 0.30$ (empty triangles). For all runs, chl = 0.3 mg m$^{-3}$ and $\lambda = 532$ nm.
A general increase of path radiance weights with bottom albedo was observed in all LLS sensors simulations (Fig. 3.5a, Fig. 3.6a-b), and preferentially in the far-range of each receiver. Likewise, path radiance contribution in the near-range of FOV was consistently greatest in those runs with smallest FOV values and longest ranges from the target. Note that target weights reaching the LLS receivers were also higher with brighter bottoms (Fig. 3.5b, Fig. 3.6c-d).

Fig. 3.6: Effect of bottom albedo on ROBOT performance: a-b) path radiance for UUV\textsubscript{Z} = 1 (left panel) and 5 m (right panel), $\rho = 0.05$ (solid rectangles), $\rho = 0.15$ (solid circles), and $\rho = 0.30$ (solid triangles). c-d) total signal for UUV\textsubscript{Z} = 1 (left panel) and 5 m (right panel), $\rho = 0.05$ (empty rectangles), $\rho = 0.15$ (empty circles), and $\rho = 0.30$ (empty triangles). For all runs, chl = 0.3 mg m\textsuperscript{-3} and $\lambda = 532$ nm.

In general, path radiance was relatively more important than target contribution for darker bottoms. For instance, the fraction of non-target weights in FILLS decreased
from 93 to 89% as the LLS was moving from a seagrass type of bottom to a sandy substrate.

Therefore, the net signal at the receiver of FILLS increased slightly as the UUV moved from bottoms with low reflectance ($\rho = 0.05$, $S/N = 0.89$) to bottoms with intermediate reflectance ($\rho = 0.15$, $S/N = 1.33$). Curiously, the detection ability deteriorates over even brighter bottoms ($S/N = 1.22$), perhaps because of increased bottom-reflected photons scattered into the sensor by the medium. For different albedos, path radiance contributions to LSF of FILLS (hypothetical CCD) and ROBOT ($UUV_z = 5 \text{ m}$) were very similar in the near-range viewing direction (Fig. 3.5a, Fig. 3.6b).

Interestingly, path radiance contribution when ROBOT was situated very close to the target was comparable between a mixed-substrate bottom with intermediate reflectance and a sandy bottom ($\rho = 0.3$) (Fig. 3.6a). $S/N$ values of ROBOT with a $UUV_z$ of 1 m were heavily influenced by bottom type (Fig. 3.6c). Approximately a 50% improvement on detection was calculated for a 3-fold change of bottom albedo from darker to brighter values. When ROBOT was positioned at 5 m above the bottom, target detection performance was not significantly affected by bottom albedo differences ($S/N \sim 5.6$) (Fig. 3.6d).

3.4 Effect of different laser wavelengths

Variation of target detection capability of LLSs with light source characteristics is described below. Likewise, the relative importance of sunlight interference on laser measurements for a specific wavelength is also investigated. Before presenting how LSF is affected by spectral changes of the laser source, one should identify ‘transparency windows’ (i.e. spectral regions where minimum light attenuation is expected) (Table 2.3).

Although the importance of different optical constituents to light attenuation vary between ‘clear’ and ‘turbid’ waters, values of $c$ are consistently lower at 532 nm than at 400 or 620 nm. When chl = 0.3 mg m$^{-3}$, the primary light attenuation component is water as a consequence of significant light scattering at 400 nm and absorption at 620 nm. As
the water becomes more turbid due to chl increases, phytoplankton absorption at blue wavelengths accounts for a considerable fraction of \(c\). In FILLS, path radiance contributions over the 1-pixel receiver was largest at 620 nm (~96%) whilst the minimum was obtained using a green laser (~90%) (Fig. 3.7).

![Fig. 3.7: Effect of laser wavelengths on FILLS performance: a) path radiance of a hypothetical multiple-pixel sensor (left axis), for \(\lambda = 400\) nm (solid rectangles), \(\lambda = 532\) nm (solid circles), and \(\lambda = 620\) nm (solid triangles); integrated weights over one-wide pixel (right axis) are indicated with a constant value for \(\lambda = 400\) nm (dotted line), \(\lambda = 532\) nm (thin solid line), and \(\lambda = 620\) nm (thick solid line). b) total signal, for \(\lambda = 400\) nm (empty rectangles), \(\lambda = 532\) nm (empty circles), and \(\lambda = 620\) nm (empty triangles). For all runs, chl = 0.3 mg m\(^{-3}\) and \(\rho = 0.15\).]"
In general, spectral differences on path radiance contributions were more defined in those spatial bins distant from the target center. An exception was found during ROBOT simulations (UUV$_Z$ = 1 m) (Fig. 3.8a) where path radiance spikes at 400 nm and 532 nm were concentrated at 0 and 10 cm from the target center and towards the far-range of the LLS receiver. In general terms, LSF shape for total signal was quite similar for a laser source of 400 and 620 nm in both sensors (Fig. 3.7b, Fig. 3.8c-d).

Fig. 3.8: Effect of laser wavelengths on ROBOT performance (‘clear water’): a-b) path radiance for UUV$_Z$ = 1 (left panel) and 5 m (right panel), $\lambda$ = 400 nm (solid rectangles), $\lambda$ = 532 nm (solid circles), and $\lambda$ = 620 nm (solid triangles). c-d) total signal for UUV$_Z$ = 1 (left panel) and 5 m (right panel), $\lambda$ = 400 nm (empty rectangles), $\lambda$ = 532 nm (empty circles), and $\lambda$ = 620 nm (empty triangles). For all runs, chl = 0.3 mg m$^{-3}$ and $\rho$ = 0.15.

In turbid waters, only ROBOT simulations 1 m above the target evidenced S/N values above one (Fig. 3.9). At $\lambda$ = 400 nm, the path radiance contribution was larger adjacent to the target center whilst proportion of background photons increased to the
edge of the image produced by ROBOT when the laser source used corresponded to longer wavelengths (Fig. 3.9a). Shorter wavelengths had the highest path radiance contribution to total signal (up to 90% at 10 cm of the target center in the far-range of the ROBOT receiver) (Fig. 3.9b).

Fig. 3.9: Effect of laser wavelengths on ROBOT performance (‘turbid water’). Similar to Figure 3.8 but chl = 5.0 mg m⁻³, ρ = 0.15 and UUV_Z = 1 m.

In terms of target detection sensitivity, green had the best overall performance in both LLS sensors even though a red source can slightly more sensitively discriminate bottom objects in eutrophic waters (S/N in ROBOT = 7.15, UUV_Z = 1 m) (Fig. 3.10). However, some interference might be expected due to solar-pumped fluorescence of phytoplankton and perhaps other targets (e.g., macroalgae, seagrass). For ROBOT, a green laser was particularly advantageous near the bottom where the net signal was
amplified up to 4 times (S/N at 532 nm = 164.5) with respect to the blue channel (S/N at 400 nm = 40.5) (Fig. 3.10a).

Fig. 3.10: Target detection sensitivity as a function of laser wavelength: a) ROBOT measurements in clear (chl = 0.3 mg m\(^{-3}\), UUV\(z\) = 1, 5 m) and turbid (chl = 0.3 mg m\(^{-3}\), UUV\(z\) = 1 m) waters and three laser source wavelengths (400, 532 and 620 nm)(S/N is computed as the ratio between target and path radiance photons in the middle pixel of the target). b) FILLS, only simulations in clear waters had S/N>1, S/N is derived as the ratio between total signal and path radiance contributions at the LLS receiver.
A blue laser source definitely was not a suitable option for LLS measurements in clear or turbid waters with respect to the path radiance contributions above discussed. For all wavelengths tested, ROBOT was superior ability in distinguishing targets over FILLS. Interestingly, S/N values were comparable between ROBOT UUVZ = 5 m (chl = 0.3 mg m^{-3}) and ROBOT UUVZ = 1 m (chl = 5 mg m^{-3}). Path radiance was greater than target photons when ROBOT was situated at 5 m above the bottom in turbid waters. In ROBOT (UUVZ = 1 m), level of detection in turbid waters was reduced as much as 30-fold compared with that measured in clear waters. The laser simulations described above assume night-time conditions (i.e., the only light source is the laser). Solar illumination during diurnal surveys introduces an additional photon component at the LLS receiver. For the sake of simplicity, sunlight interference was analyzed for the one-pixel sensor (FILLS) as a function of sun altitude and spectral composition (Fig. 3.11). Values on Figure 3.11 represent maximum estimations because initial photon quantities were 1 and 0.4 W for solar and laser sources, respectively. In general, ambient path radiance contribution with respect to laser target signal increases as the sun approaches the zenith (Fig. 3.11a). This trend is less pronounced at higher turbidities because the underwater light field becomes more diffuse. Moreover, for a fixed solar altitude above the horizon, FILLS detector collects a greater proportion of sunlight photons when the water is more turbid. As expected, FILLS measurements using a green laser were highly affected by sunlight photons due to its proximity to the sea-surface (Fig. 3.11b). Likewise, sunlight interference on laser measurements decreases for brighter targets (see Fig. 3.11a-b, \( \theta_{\text{sun}} = 29.5^\circ, \lambda = 532 \text{ nm} \)). At 620 nm, the influence of solar photons on LLS signal was minimal.

3.5 Applications
3.5.1 Microenvironments with significant resuspension

UUUV missions using laser line scanners may encounter waters with different proportions of organic and mineral particles or even different particle spectra (e.g., variations of particle assemblages within the bottom boundary layer).
Fig. 3.11: Variation of laser signal in FILLS due to sunlight contributions: a) Proportion of sunlight/laser photons at the receiver of LLS (one-wide pixel) as a function of sun zenith angle and water turbidity, chl = 0.3 mg m\(^{-3}\) (empty rectangles, left axis), chl = 5.0 mg m\(^{-3}\) (solid rectangles, right axis), \(\rho = 0.30\) and \(\lambda = 532\) nm. b) Spectral contributions of laser and sunlight components at the LLS receiver, \(\rho = 0.15\), chl = 0.3 mg m\(^{-3}\), and \(\theta_{\text{sun}} = 29.5^\circ\). In all cases \(C = 0\) and \(f_s = 21\%\).

Signal modifications at the FILLS receiver associated with waters of different indices of refraction (real part) are depicted in Figure 3.12.
In general for a CCD-like receiver, path radiance of FILLS was more concentrated near the target center for organic-enriched ($n_p = 1.02$) than for mineral-enriched particle populations ($n_p = 1.26$) (Fig. 3.12a). Notice that the original FILLS detector cannot discriminate photon distributions around the illuminated spot because it...
has only one viewing pixel resolution. Non-target photons reaching the detector were more than 2-fold greater in TYPE I than in TYPE II waters, and their contribution to total integrated signal was higher in TYPE I (~80.6%) than in TYPE II (~64.4%) waters (Fig. 3.12b). Similar to FILLS, path radiance photons of ROBOT LSF increased as long as the index of refraction of particles increased (Fig. 3.13a).

Fig. 3.13: Effect of particle composition on ROBOT performance: a) path radiance for TYPE I (circles) and TYPE II (rectangles) particle populations. b) total signal for TYPE I (circles) and TYPE II (rectangles) particle populations. In all cases UUVZ = 7 m, \( \lambda = 532 \) nm, \( \rho = 0.3 \), and \( \text{chl} = 0.3 \) mg m\(^{-3} \).

However, path radiance was a smaller fraction of total signal in ROBOT with respect to FILLS (Fig. 3.13b). Consequently, S/N values of ROBOT were circa 8-fold greater than FILLS. Slope of total signal estimated from the target center to the far-range
FOV edge was more variable in ROBOT than in FILLs (hypothetical CCD) (Fig. 3.12b, Fig. 3.13b). Likewise, a greater variation of S/N values due to \( n_p \) (~25%) changes was estimated for ROBOT (~50%) than for FILLs (~16%), probably due to finer pixel resolution. Variation of LSF with different sized particle distributions at the receiver of FILLs is presented in Figure 3.14.

![Graph](image1)

**Fig. 3.14:** Effect of particle-size distributions on FILLs performance: a) path radiance of hypothetical multiple-pixel sensor (left axis) for TYPE III (circles) and TYPE IV (rectangles) particle populations; integrated weights over one wide pixel (right axis) are indicated with a constant value for TYPE III (dotted line) and TYPE IV (solid line) particle populations. b) total signal for TYPE III (circles) and TYPE IV (rectangles) particle populations. In all cases UUVz = 7 m, \( \lambda = 532 \text{ nm} \), \( \rho = 0.3 \), and chl = 0.3 mg m\(^{-3}\).
In FILLS, total path radiance integrated over a one-pixel receiver was circa 2-fold larger when runs were made with large particle populations (Fig. 3.14a). In far-range pixels of a hypothetical CCD, large-particle populations ($\xi = 3.1$) had a greater path radiance contribution than small-particle populations ($\xi = 4.0$). Nevertheless, non-target weights of smaller-sized particles were larger in near-range pixels (Fig. 3.14a). This effect was not evident in LSF of total signal (Fig. 3.14b). Likewise, relatively small particle assemblages affected more drastically the shape of path radiance LSF by inflicting a flattening on weights collected along the receiver viewing direction. For near-range pixels of ROBOT ($UUV_Z = 5$ m), there was not a significant path radiance difference between particles assemblages with different size (Fig. 3.15a).

Fig. 3.15: Effect of particle-size distributions on ROBOT performance: a) path radiance for TYPE I (circles) and TYPE II (rectangles) particle populations, b) total signal for TYPE I (circles) and TYPE II (rectangles) particle populations. In all cases $UUV_Z = 7$ m, $\lambda = 532$ nm, $\rho = 0.3$, and chl = 0.3 mg m$^{-3}$. 
Similar to FILLS, the performance of ROBOT for detecting targets in environments with relatively small particle populations was superior to those cases where coarser particle populations dominate (Fig. 3.15b). However due to the greater path radiance contribution in FILLS (>62%), FILLS had a noisier (~2-fold) signal than ROBOT (S/N~43). Overall, changes in particle spectra (~29 % variation of Junge slope) had a more significant influence on S/N values of ROBOT (~12%) than on FILLS (~8%).

3.5.2 Coral reef ‘halo’

In Figure 3.16 is simulated an LLS transect across a theoretical ‘halo’ surrounding a coral patch.

Fig. 3.16: Bottom albedo algorithms for LLSs: a-c) ROBOT, clear water, UUVZ = 1 m (circles) and 5 m (rectangles); turbid water, UUVZ = 1 m (triangles), parabolic model (dotted lines). d) FILLS, clear water (circles), linear model (dotted line). In all cases $\lambda = 532$ nm. Unlike FILLS, signal indices for ROBOT are path radiance corrected. Note the non-zero intercept for FILLS.
Notice that there is a range of reflectance values as the UUV is passing over sandy sediments (inner part of the ‘halo’, \( \rho = 0.3 \)), mixed-bottom types (transition boundary, \( \rho = 0.15 \)), and dark substrates such as sea-grass beds (outer part of the ‘halo’, \( \rho = 0.05 \)). For ROBOT at 1 m above the target, the slope between path radiance-corrected signal and bottom albedo was greater for clear than for turbid waters (Fig. 3.16a-c, Table 3.2).

Table 3.2: Curve fitting parameters for different bottom albedo retrieval functions.

ROBOT model: \( y_1 = a_0 + a_1 X + a_2 X^2 \), \( a_0 = 0 \), where \( y \) stands for \( W_{\text{max}}-W_{\text{min}} \) (near) (first row), \( W_{\text{max}}-W_{\text{min}} \) (far) (second row), and \( W_{\text{max}} \) (third row). FILLS model: \( y_2 = m_1 X + b_1 \), where \( y_2 \) is the total signal at the sensor. ROBOT1: \( UUV_Z = 1 \text{ m}, \text{chl} = 0.3 \text{ mg m}^{-3} \), ROBOT2: \( UUV_Z = 5 \text{ m}, \text{chl} = 0.3 \text{ mg m}^{-3} \), ROBOT3: \( UUV_Z = 1 \text{ m}, \text{chl} = 5 \text{ mg m}^{-3} \). In FILLS \( \text{chl} \) is 0.3 mg m\(^{-3}\). Between parentheses is one standard error. Values \( a_2 \) must be divided by 1,000. All models explained above 99% variability of simulated data.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>ROBOT1</th>
<th>ROBOT2</th>
<th>ROBOT3</th>
<th>FILLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_1 )</td>
<td>8.084 (0.033)</td>
<td>1.438 (0.017)</td>
<td>3.283 (0.363)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6.038 (0.406)</td>
<td>0.778 (0.165)</td>
<td>2.484 (0.384)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>8.295 (0.006)</td>
<td>1.800 (0.006)</td>
<td>3.346 (0.367)</td>
<td></td>
</tr>
<tr>
<td>( a_2 )</td>
<td>1.29 (1.19)</td>
<td>49.1 (14.8)</td>
<td>1.31 (0.24)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.95 (0.63)</td>
<td>-4.09 (6.03)</td>
<td>0.51 (0.22)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-33.2 (13.3)</td>
<td>-27.6 (14.0)</td>
<td>-34.2 (13.4)</td>
<td></td>
</tr>
<tr>
<td>( m_1 )</td>
<td>-33.2 (13.3)</td>
<td>-27.6 (14.0)</td>
<td>-34.2 (13.4)</td>
<td>10.97 (0.140)</td>
</tr>
<tr>
<td>( b_1 )</td>
<td></td>
<td></td>
<td></td>
<td>49.44 (2.746)</td>
</tr>
</tbody>
</table>

ROBOT detection was also less influenced by changes of bottom reflectance when LLS measurements were obtained at larger distances (\( UUV_Z = 5 \text{ m} \)) from the target. In general, parabolic functions were the most satisfactory models for ROBOT \( \rho \)-
LSF curves whilst linear regressions seemed to explain better FILLS curves. Overall, the Wmax-Wmin (far) algorithm provided the most linear ROBOT results (smallest 2\textsuperscript{nd}-order term) for the different water and observational conditions, although Wmax-Wmin (near) was most linear for 1m, clear-water settings.

Unlike ROBOT, FILLS fits were not forced through the zero $\rho$ value because it is not possible to estimate and eliminate path radiance in the original sensor from LLS measurements. However, path radiance in FILLS could be estimated at $\rho = 0$ because the intercept was significantly different from zero ($P<0.035$, $t$-Student = 18). For this particular exercise, estimated FILLS path radiance may contribute to total signal between 10 ($\rho = 0.30$) and 50% ($\rho = 0.05$).
4 Conclusions

As a preliminary step before modeling laser-line-scanner performance for detecting underwater targets, a 1-D Monte Carlo model was built and validated. The elemental pieces to construct the one-dimensional MC were derived from the model originally proposed by Reinersman and Carder (2004). Similar to MC1D, HyMOM (3-D Hybrid Marine Optical Model, Monte Carlo) was validated against Hydrolight using the same type of waters with low (0.3 mg m\(^{-3}\)) and high (5.0 mg m\(^{-3}\)) chlorophyll \(a\) concentrations (i.e., a wide range of water transparencies). When irradiances were analyzed, RMSlog differences between MC1D and Hydrolight for clear and turbid waters were comparable to those found between HyMOM and Hydrolight irradiances (chl: 0.3 mg m\(^{-3}\), \(E_d = 0.98\%\), \(E_u = 1.28\%\); chl: 5 mg m\(^{-3}\), \(E_d = 2.36\%\), \(E_u = 3.63\%\)). Similar to underwater irradiances, comparisons between \(E_{u0+}\) values calculated by MC1D and Hydrolight also showed less agreement in turbid waters than in clear waters. More uncertainty in less transparent waters is primarily related to the increase of variance caused by fewer photons reaching the detector and the need for more photons to maintain the same signal-to-noise ratio. General comparisons of various Monte Carlo models against Hydrolight were reported by Mobley et al. (1993) for 1-D scenarios, with MC methods suffering in comparison at very deep ocean depths and in upwelling radiance or irradiance comparisons at any depth due to signal-to-noise considerations.

Comparisons of \(L\) values between MC1D and Hydrolight models were not made because the way these two models are specified varies in many aspects (Reinersman and Carder, 2004). For instance, the unit sphere in MC1D is partitioned into 100 \(\theta\) bins whilst Hydrolight considers 10 \(\theta\) quads over 85° and polar caps of 5°. Furthermore, the direct solar beam is distributed from 29° to 30° in MC1D and from 25° to 35° in Hydrolight.
Although MC1D has better directional resolution than Hydrolight, more variance (less photon weights are tallied) is expected in final radiance estimates using MC1D. Angular-bin resolution differences between MC1D and Hydrolight also affects internal sub-surface reflections and could also account for differences of radiance values for these two models (Reinersman and Carder, 2004). As suggested by Reinersman and Carder (2004), the above variations on algorithm structures may also explain the differences observed between MC1D and Hydrolight for irradiance estimations.

Based on MC1D, a 2-D Monte Carlo model was successfully implemented in this work to model target detection and the effect of various oceanographic conditions on S/N values of two continuous laser line scanners: ROBOT and FILLS. These optical instruments are currently in use and were first conceived to facilitate the identification of mine-like contacts and to address environmental issues such as mapping of coral reefs (Strand et al., 1996; Strand, 1997; Kaltenbacher et al., 2000). Likewise, ROBOT and FILLS are ideal systems to automatically detect and classify objects of interest in clustered bottoms (e.g., coral reefs) where acoustic techniques fail. They represent cheaper and more accurate solutions than human recognition of diverse and numerous underwater targets.

ROBOT and FILLS have been designed for different purposes. ROBOT allows morphologic characterization of bottom features in 3-D whilst FILLS is not able to retrieve bottom 'shape' even though it may detect simultaneous fluorescence signatures (inelastic scattering) at various wavelengths. Robustness of 2-D LLS models was tested by comparing modeled and measured (aquarium experiments) line spread functions. The model imitated very well the shape of ROBOT LSF and it was able to capture geometric characteristics such as the bi-static configuration between the source and the receiver (see Figure 3.2).

A typical feature in all simulations (more pronounced in hypothetical FILLS) was the asymmetric LSF with more photon weight concentrated in far-range pixels with respect to the sensor viewing direction. This effect was likely related to its greater path radiance contribution with respect to total signal. Those pixels closer to the sensor have a minor backscattering component originating from the main laser beam, thus path radiance is reduced compared to those pixels situated beyond the target. In near-range pixels,
multiple scattering off the target (forward scatter and then target reflectance or vice versa) is the largest path radiance component.

Simulations in 2-D clearly confirmed that ROBOT and FILLS are useful optical devices for target detection in clear waters and for highly-reflective bottoms. Thus, it is not surprising that most oceanographic studies using LLSs have been planned in clear tropical waters with sandy bottoms such as those found in the Bahamas Islands (e.g., FILLS, Mazel et al., 2003). For different environmental conditions (e.g., turbidity) and UUV altitudes above the target, ROBOT produced a sharper image than FILLS due to parallax that reduces contributions due to backscattered photons (Table 4.1). For instance at 7 m above the target, ROBOT efficiency to recognize objects was two-fold superior to FILLS. Also notice the S/N degradation caused by a greater path radiance in turbid waters for FILLS may represent 100% of the signal reaching the sensor.

Table 4.1: Summary of laser line scanner SNR performance for target detection. chl = mg m$^{-3}$, S/N calculated as target/path radiance contributions. ROBOT1, ROBOT2 and ROBOT4 have UUV$_Z$ of 1, 5 and 7 m, respectively.

<table>
<thead>
<tr>
<th>chl</th>
<th>ROBOT1</th>
<th>ROBOT2</th>
<th>ROBOT4</th>
<th>FILLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.3</td>
<td>253.4</td>
<td>5.6</td>
<td>2.0</td>
<td>1.2</td>
</tr>
<tr>
<td>5.0</td>
<td>10.46</td>
<td>&lt;1</td>
<td>&lt;1</td>
<td>&lt;1</td>
</tr>
</tbody>
</table>

As was demonstrated, far-range viewing photons at the receiver of ROBOT can be subtracted from the signal with the largest target contribution (central pixel of CCD) to remove much of the path radiance contribution. Hence, noise due to underwater optical variability in ROBOT measurements may be filtered in real-time. Assuming a flat bottom within the ROBOT FOV and after path radiance correction, LSFs would still experience changes that can be interpreted by differences as bottom reflectivity changes (bottom albedo retrieval capability).
Unfortunately, *in situ* path radiance measurements could not be derived analyzing FILLs signals unless this original sensor is further sub-divided into multiple pixels (see above hypothetical CCD) similar to the ROBOT receiver. FILLs, using a one-pixel FOV, sees simultaneously photons coming from the target and the propagation medium. Thus, the only way to estimate which fraction of the total FILLs signal is caused by non-target photons is by modeling path radiance using known (measured) IOPs and apparent optical properties. Even doing that, $\rho$-LSF relationships found in this work suggest that ROBOT is more discriminative of bottom-albedo discontinuities than FILLs.

Simulations analyzing spectral effects on S/N values at the LLS receiver consistently showed that a green laser is the best all-around choice to detect targets in marine waters. In turbid waters, target discrimination using red ($\lambda = 620$ nm) and green ($\lambda = 532$ nm) laser sources was comparable. In estuarine waters red lasers are widely used (Moore et al., 2000) whilst in shallow reef systems (typically oligotrophic and transparent waters) a green source is more recommended for nocturnal work (Carder et al., 2001). LLS measurements during daylight hours (e.g., night-time schedule is full for inspection of ships hulls) are sometimes mandatory even though the effect of solar illumination on target detection can be detrimental. For instance, the mapping of light fields under ships can take place during daylight hours since ambient down-welling irradiance can be 3.5 orders of magnitude smaller than at the sea surface (Reinersman et al., 2004).

MC results from this work indicated that the greatest interference of ‘green’ sunlight photons on total signal reaching the LLS receiver occurs around noon when no ship is present to block ambient photons reaching the bottom. Thus, longer laser wavelengths ($\lambda = 620$ nm) and mid-morning/mid-evening measurements would be the most suitable choice when the target to be detected lay in open areas (e.g., no objects shading the target) and near the bottom, if night-time surveys are not possible, water turbidity is relatively high, and detection range is comparably short (strong attenuation of ambient red wavelengths due to water itself).

In that regard, an alternative solution to get rid of ‘green’ photons is the use of fluorescence channels in FILLs, although solar-induce bottom fluorescence would also be present. The FILLs excitation channel does not match the spectral filter of the
receiver, so path-scattered laser photons are not ‘seen’ by fluorescence detectors. However, fluorescence measurements may also encounter difficulties such as interference due to solar-pumped variations (excitation energy of sun changes as FILLs is moved away from the sea-surface) and phytoplankton fluorescence contributions.

For the same water turbidity, bottom reflectance and detection wavelength, LLS signals can also be affected by changes in particle size distribution and composition. For instance, LLS measurements in high-energy environments (e.g., exposed beaches, shallow coastal waters highly influenced by wind) would be modified by aggregation and breakup of particle aggregates (Milligan, 1995). Simulations considering measurements of FILLs and ROBOT in waters with different particle assemblages were assessed using a forward method of inversion of the VSF. The Fournier-Forand phase scattering function allowed the generation of artificial VSFs considering contrasting cases of particle assemblages with various origins (mineral vs organic) or size distributions. In general, both mineral-dominant and small-size particle populations produced a flattening of LSF obtained at the LLS receiver (e.g. less forward and more side and back scattering. Likewise, they allowed a better LLS performance because path radiance of larger organic particles preferentially scattered in the forward direction with respect to small mineral particles, thus noise (mostly forward-scattered photons before and after bottom reflection) was concentrated in the neighborhood of the target center. In that regard, source-receiver inclination of ROBOT makes ROBOT measurements less vulnerable to path radiance than FILLs in environments with larger, organic-enriched particles.

The real part of the index of refraction of particles, $n_p$, had the largest effect on total signal variability because of the greater dependency of particle backscattering efficiency on $n_p$ (Mobley et al., 2002). In nature $n_p$ and $\xi$ (Junge size-distribution parameter) bulk properties result from a complicated matrix of particles that makes more diffuse the idea of defined particle populations. For instance, transparent exopolymers in marine snow increases $n_p$ as bacteria with slighter higher $n_p$ (1.04-1.07) attach to it (Costello et al., 1995). Likewise relatively dehydrated organic particles may result in larger $n_p$ values (e.g., fecal pellets of copepods) (Twardowski et al., 2001). Since Mie theory assumes sphere-type particles, an additional complication is introduced when non-
spheres (spheroids) are measured (~ 30% deviation from the maximum scattering) (Herring, 2002). The study of the bottom boundary layer (BBL) has recently become a favorite natural lab to test different np and ξ models (see Boss et al., 2001) and represents the ideal place to investigate LLS models in connection with different particle assemblages. In this scenario, np increases near the bottom due to more inorganic particles, and ξ has the opposite trend because of the greater abundance of larger particles near the sea bed (more vertical mixing energy). In the other hand, fine organic particles with low settling velocities are dominant further from the BBL (Boss et al., 2001). Therefore, np and ξ effects on FILLS/ROBOT line spread function could cross-compensate, and no differences in LSF shape would be expected due to changes of particle populations along the path between the AUV and the target. Furthermore, since ROBOT was more sensitive to np changes (\(\tilde{h}_{bp}\) variability accounted mainly by np) than FILLS, FILLS would be a better option to target detections in waters with drastic changes in \(\tilde{h}_{bp}\) (e.g., changes on BBL thickness, channel-shallow transitions in an estuary).

Choosing the most convenient laser line scanner (ROBOT vs FILLS) will depend on the application and in what environments these systems will be deployed. The main limitations of FILLS are: a) relatively large interference of elastic path radiance (larger noise per pixel at the receiver), b) lack of 3-D mapping, and no underway bottom albedo retrievals, and c) the larger cross-track spatial resolution of detector. However, ROBOT is more influenced by solar photons and must be reconfigured to perform inelastic measurements (fluorescence). MC models proposed in this work answer many questions regarding target detection capabilities of each kind of LLS studied and for different types of waters or meteorological conditions. Nevertheless, further refinements will be required to explore inelastic-based signals (e.g., fluorescence in FILLS), 3-D receivers and targets, and the effect of multiple laser beams (e.g., fan-type lasers such ROBOT) on LSF. Likewise, no major advances for LLS models would be possible without field measurements.
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