Shallow Water Remote Sensing
John Hedley, IOCCG Summer Class 2018

- Overview - different methods and applications
- “Physics-based” model inversion methods
- High spatial resolution imagery and Sentinel-2
- Bottom mapping
- Satellite derived bathymetry (SDB)

- Sun-glint correction of high spatial resolution images
- Model inversion methods and uncertainty propagation
Objectives of shallow water remote sensing

- Bottom mapping
  - corals, seagrasses, macroalgae
- Water optical properties
- Bathymetry (depth)

Applications

- Spatial ecology (science)
- MPA design (resource mapping)
- Assessing ecosystem services
  - coastal protection and stabilisation
  - fisheries, local subsistence
  - blue carbon
  - tourism
Applications on coral reefs and similar environments

- Need higher spatial resolution than typical ocean colour satellites

Hedley et al. 2016, Remote Sensing, 8, 118; doi:10.3390/rs8020118
Hedley et al. 2018, RSE Sentinel-2 special issue (in press, probably)
WorldView-2 image of Yucatan coast, Mexico (15 Feb 2008)
(pixels < 2 m, 8 bands, ~5 usable)

(c) DigitalGlobe
High Spatial Resolution Imagery

Pixel size $< 5 \text{ m}$
- Many past and present (archive imagery still available)
- Pleiades, WorldView-2, 3, QuickBird, GeoEye, IKONOS, RapidEye, Kompsat
- Typically 4 bands, R, G, B and NIR, but WorldView has 8 bands

Pixel size $10 - 30 \text{ m}$
- SPOT (various)
- Landsat 8 (30 m)
- Sentinel 2 (10 m in four bands)

Notes:
- Radiometric calibration on commercial satellites is usually not as good as on space agency satellites.
- For these sensors bands are spectrally wide, not narrow as with ocean colour satellites
  - not always appropriate to just use centre wavelength
  - may need to integrate over wavelength
WorldView-2 image of Yucatan coast, Mexico (15 Feb 2008)
pixels < 2 m, 8 bands, ~5 usable

(c) DigitalGlobe
Sentinel-2 image of Yucatan coast, Mexico (17 April 2018)
(pixels 10 m, ~5 usable bands)
Sentinel 2 - useful bands are at different resolutions

<table>
<thead>
<tr>
<th>Band</th>
<th>Wavelength range</th>
<th>Pixel size</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>433 – 453 nm</td>
<td>60 m</td>
</tr>
<tr>
<td>02</td>
<td>457 – 523 nm</td>
<td>10 m</td>
</tr>
<tr>
<td>03</td>
<td>542 – 578 nm</td>
<td>10 m</td>
</tr>
<tr>
<td>04</td>
<td>650 – 680 nm</td>
<td>10 m</td>
</tr>
<tr>
<td>05</td>
<td>697 – 713 nm</td>
<td>20 m</td>
</tr>
<tr>
<td>06</td>
<td>732 – 748 nm</td>
<td>20 m</td>
</tr>
<tr>
<td>07</td>
<td>773 – 793 nm</td>
<td>20 m</td>
</tr>
<tr>
<td>08</td>
<td>784 – 900 nm</td>
<td>10 m</td>
</tr>
<tr>
<td>8A</td>
<td>855 – 875 nm</td>
<td>20 m</td>
</tr>
<tr>
<td>09</td>
<td>935 – 955 nm</td>
<td>60 m</td>
</tr>
</tbody>
</table>

→ Interesting potential issues / artefacts
Methods for bottom mapping and/or bathymetry

Many and very diverse – overlap with terrestrial methods

Empirical, image based, requires training from in-situ data
• Classification, depth invariant indices
• Bathymetry by regression methods

Physics based
• Radiative transfer model inversion

Hybrid
• Object orientated techniques - classification combined with rules which can take data from other remote sensing and physics based methods
• e.g. depth, wave energy (wind)
Empirical image based methods (e.g. bathymetry)

- Usually assume exponential attenuation of light with depth (i.e. constant $K_d$)
- Requires training of points from imagery (deep water, known depths etc.)
- Similar methods for water column correction, change detection, etc.

Lyzenga 1978

\[ X_i = \ln(L_i - L_{si}) \]
\[ Z = a_0 + a_iX_i + a_jX_j \]

Stumpf et al. 2003

\[ z = m_1 \frac{\ln(nR_w(\lambda_i))}{\ln(nR_w(\lambda_j))} + m_0 \]

$X_i, a_0, a_1, a_2$ from regression

$m_0, m_1$, from regression

![Depth images](image)
Benthic classification example, Lizard Island, GBR

Key:
- **Deep Water**
- **Medium Seagrass**
- **Rubble / Sparse Coral**
- **Sand**
- **Dense Seagrass**
- **Reef Matrix**
- **Land**
Classification

- Works by identifying pixels that have similar spectral reflectances
- Supervised or unsupervised
- Need for water column correction

One method - depth invariant indices

\[ X_i = \ln(R_i - R_{i\text{deep}}) \]

\[ X_i = \left( \frac{k_i}{k_j} \right) X_j + d_{ij} \]

only need ratio of attenuation coefficients can extract from image using sand at different depths
Sun-glint: different types of glint dependent on spatial scale

Large images e.g. MERIS, pixels > 100 m
→ function of solar-view geometry and sea state

High spatial resolution, pixels < 10 m
→ individual waves

Eg. IKONOS, QuickBird, WorldView 2, Sentinel 2
Atmospheric contribution and surface glint

Figure 1: Three-way decomposition of photon paths underlying the atmospheric correction algorithm, * - indicates a scattering event. (a) Direct transmission and reflection from a black ocean; (b) Path radiance over a black ocean; (c) Total transmission of water penetrating photons. Note that a combination of multiple bottom boundary interactions from (b) and (c) is also possible.

1) Direct Glint  2) Atmospheric Reflectance  3) Part We Want
Glint prediction and correction - large scale

Cox and Munk equations

• 1950s - based on photographs of surface glitter
• Many subsequent studies: all agree


Result is statistical model of the sea surface:

**Mean square slope** = \(0.003 + 0.00512 \, U_{10}\)

Sun-glint depends only on:
1) sun position
2) sensor position
3) wind speed (and to a small extent wind direction)

• Statistical description at large scales and open ocean \(\rightarrow\) large pixels (100s m)
• No use for high resolution imagery and shallow areas
High spatial resolution

- Atmospheric contribution may be assumed uniform over the area of interest
- Surface glint is not uniform
Glint correction or “deglint” of high spatial resolution images

- Can correct using a Near-Infra Red (NIR) band to assess the glint
- **Assumption 1** - Glint has a uniform spectral signature
- **Assumption 2** - NIR from below the water surface is zero

- Start with a sample of pixels over deep water, where it is assumed there is no sub-surface variation in reflectance
Glint correction or “deglint” of high spatial resolution images

Sample over deep water

NIR reflectance (or SWIR)

and other similar methods - see Kay et al. (2009) *Remote Sensing* 1: 697-730
Glint correction or “deglint” of high spatial resolution images

Sample over deep water

\[ R'_i = R_i - b_i(R_{NIR} - \text{Min}_{NIR}) \]

- Before or after atmospheric correction? – using minimum NIR reflectance means it probably doesn’t matter if you assume uniform atmospheric contribution
Before deglint
After deglint
Deglint example (Landsat 8)
Deglint example (Landsat 8)
Note 1: Glint corrected images are quite noisy

1) Signal to noise issue - take a big signal away to leave a small signal, but noise was on the big signal.
2) Also, combining noise from two bands - visible band and NIR band.
3) Process is not perfect - band alignment, etc.

→ Spatial filtering (smoothing) may be useful
Note 2: The need for precise band alignment

- Image bands are not always perfectly spatially aligned
- Causes serious problems for glint removal algorithm
- WorldView-2 has various striping artefacts
  - glint corrected
  - band alignment on right side is bad

- Sentinel-2 detector edges – similar problems
Note 3: Over-correction when NIR below surface is not zero

• Assumption of zero NIR from below the water is not valid in shallow water
• Result is “dark halo” effect around land features
• Causes problems for subsequently applied algorithms

Before

After
Problem of sub-pixel glint (Sentinel-2)

Sea surface undulations occur at multiple scales
- From 100’s metres to millimetres
- 10 m pixels may still contain slopes contributing to the glint within them
Specific challenges with Sentinel-2

Pixel size means hard to get a “no glint” reference

The darkest pixels probably still contain some glint
So glint correction is incomplete and there remains a glint contribution
Specific challenges with Sentinel-2

Pixel size means hard to get a “no glint” reference

Force correction to assume zero NIR reflectance rather than empirical minimum

But that assumes NIR really should be zero

- i.e. atmospheric correction has removed any aerosol contribution in the NIR
- but atmospheric corrections often use NIR to estimate aerosol!
Very difficult to disentangle glint from aerosol contribution in Sentinel-2 imagery - without additional information

Atmospheric reflectance, Marine 99% RH aerosol model (libRadtran)

- In this plot sun and view are directly overhead (zenith and nadir)
- Indirect surface reflectance but no direct glint included
- Top two lines include aerosols, bottom line Rayleigh only

SWIR doesn’t help much - there still is an aerosol and glint contribution
Harmel et al. 2018

- Glint correction for Sentinel-2
- Uses SWIR to characterise glint
- Wavelength dependence based on refractive index of water
- But still relies on a-priori separation of atmospheric reflectance from surface glint

Need this data for atmospheric correction, e.g. from AERONET station.
Effectively this adds information to reduce uncertainty between aerosol and glint

Inversion methods for shallow water applications
Shallow water models for $R_{rs}$

1) HydroLight-EcoLight

Build look-up tables for different depths, water column optical properties and bottom reflectances

Mobley et al. (2005) *Applied Optics* 44, 3576-3592

2) Semi-analytical models

Develop a simpler conceptual model and estimate coefficients or parameters from a physically exact model such as HydroLight

Results in a forward model that is faster to compute

Lee et al. (1998) *Applied Optics* 37, 6329-6338
Lee et al's semianalytical model for shallow water reflectance

\[ r_{rs}(\lambda) \approx f(P, G, X, H, \rho(\lambda), \lambda) \]

\[ a(\lambda) = a_w(\lambda) + [a_0(\lambda) + a_1(\lambda) \ln P] P - G \exp[-0.015(\lambda - 440)] \]

\[ b_b(\lambda) = b_{bw}(\lambda) + X (400/\lambda)^Y \]

\[ u(\lambda) = b_b(\lambda)/[a(\lambda) + b_b(\lambda)], \quad \kappa(\lambda) = a(\lambda) + b_b(\lambda) \]

\[ r_{rs}^{dp}(\lambda) \approx [0.084 + 0.170u(\lambda)] u(\lambda) \]

\[ D_u^C(\lambda) \approx 1.03\sqrt{1 + 2.4u(\lambda)} \quad D_u^B(\lambda) \approx 1.04\sqrt{1 + 5.4u(\lambda)} \]

\[ r_{rs}(\lambda) \approx r_{rs}^{dp}(\lambda) \left(1 - \exp\left\{-\left[\frac{1}{\cos \theta_w} + \frac{D_u^C(\lambda)}{\cos \theta}\right] \kappa(\lambda) H\right\}ight) \]

\[ + \frac{1}{\pi} \rho(\lambda) \exp\left\{-\left[\frac{1}{\cos \theta_w} + \frac{D_u^B(\lambda)}{\cos \theta}\right] \kappa(\lambda) H\right\} \]

\[ H = \text{depth in metres} \]
\[ P = \text{phytoplankton concentration (proxy)} \]
\[ G = \text{dissolved organic matter concentration (proxy)} \]
\[ X = \text{backscatter} \]
\[ Y = \text{(spectral slope of backscatter) is fixed at 1} \]

Also incorporates sun and view zenith angles

Various factors derived from HydroLight
Inversion of the model

This is a **forward model** it describes what can occur in every individual pixel based on what is in the pixel

\[ r_{rs}(\lambda) \approx f(P, G, X, H, m, E)(\lambda) \]

Six values describe every pixel

But we start with this and wish to deduce this

1) Look-Up Tables - just try every combination of \( P, G, X, H, m, E \) within their bounds and find which produces the best match for the pixel \( r_{rs}(\lambda) \)

2) Successive approximation technique such as the Levenberg-Marquardt algorithm, keeps adjusting solution to try and improve it.
LUT (look-up table)

Depth,   Phytoplankton,   CDOM, … etc
1 m      0.1 mg m⁻³
2 m      0.1 mg m⁻³
3 m      0.1 mg m⁻³
4 m      0.1 mg m⁻³
1 m      0.2 mg m⁻³
2 m      0.2 mg m⁻³
3 m      0.2 mg m⁻³
4 m      0.2 mg m⁻³
1 m      0.4 mg m⁻³
2 m      0.4 mg m⁻³
3 m      0.4 mg m⁻³
4 m      0.4 mg m⁻³

Estimate:
Depth = 2 m
Phytoplankton = 0.2 mg m⁻³
… etc
Adaptive LUT construction

TARGET FUNCTION

\[(b_1, b_2) = f(\alpha), \quad 0 \leq \alpha \leq 1\]

ADAPTIVE POINT-BASED LUT

iteration 0

\[\Delta \alpha = 0.2\]

iteration 1

\[\alpha = 0.1\]

\[\alpha = 0.3\]

iteration 2

Example slice through ALUT structure
Uncertainty Propagation

Fundamental uncertainty
→ similar spectra from differing parameters
Sources of "noise" → uncertainty

Hyperspectral deep water pixels

Reflectance

Wavelength (nm)

spectrally correlated
Propagation through inversion

- better than direct result
- spatially smoother

Image pixel

image noise
(multivariate normal)

subtract random noise term × 20 times

20 reflectance spectra

invert to retrieve parameter estimations

discard upper and lower tails to give 90% conf. intervals

use mean for actual result
Bathymetry estimation with uncertainty

CASÍ

Quickbird

= 90% confidence interval
Sentinel-2 bathymetry of Lizard Island (GBR) by model inversion

- Uses bands 1, 2, 3, 4 and 5
- ALUT inversion of Lee et al. equations
- In-situ echo-sound data for comparison
Direct result (single inversion)

200 m
Mean of 20 noise perturbed results
Single inversion vs. mean of noise perturbed inversions

- Marginally better statistics, $r^2$, mean absolute residual, etc.
- Cosmetically better (spatially smoother)
Shallow (upstanding) coral heads

- Correctly identified as being shallow even though are dark pixels
- Benefit of variable bottom reflectance in the forward model.
Uncertainty (Quickbird image)
• Dark patches (coral heads) have relatively higher uncertainty in depth.
• Because their reflectance is similar to that of deeper pixels, within the bounds defined by the noise model.
Light absorption due to CDOM

Total absorption

Estimated $a(440)$ (m$^{-1}$) vs. Measured $a(440)$ (m$^{-1}$)
Light absorption due to CDOM

![Graph showing light absorption due to CDOM](image)

**Total absorption**

- Estimated $\alpha(440)$ (m$^{-1}$) vs. Measured $\alpha(440)$ (m$^{-1}$)
Bottom reflectance

- Use the bathymetry estimate and water optical properties to make water column correction
Bottom reflectance

• Use the bathymetry estimate and water optical properties to make water column correction
Corals turn temporarily white when stressed by elevated temperature

- Key indicator of climate change stresses on coral reefs
Coral Bleaching Detection (Sentinel-2)

8 June 2016

23 February 2017
Coral Bleaching Detection (Sentinel-2)

1 km

8 June 2016

23 February 2017

Bottom Reflectance

2016

2017

bleaching
Object-orientated / machine learning techniques

- Original image
- Habitat map
- Bathymetry
- Bottom reflectance
- Environmental data (e.g. wave energy, wind)

Legend:
- Coral/Algae
- Rock
- Rubble
- Sand
- Small Reef
- PatchReefs
- DeepWater
- Deep Slope
- Deep Lagoon
- Plateau