Bathymetric mapping
using multispectral satellite imagery

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Remote Sensing of Water Depth

- **Bathymetry: an important variable**
  - Controls photosynthesis and aquatic ecosystem
  - Image correction for better habitat classification

- **Multibeam echo sounding** *(Kongsberg-Maritime EM 120)*
  - 3000 m deep
  - 150° coverage of sea floor
  - Horizontal resolution: <100 m in deep water and <3 m in shallow water

- **Bathymetric Lidar system (SHOALS)**
  - Up to 50 m deep
  - 4 to 8 m point spacing
  - ±15 cm depth accuracy and ±2 m horizontal accuracy

Bathymetric Mapping using Multi-spectral Imagery

**Advantages**
- Wide availability of data: IKONOS, QuickBird, Landsat, etc
- Low cost
- Large spatial coverage, high spatial resolution
- Derive water depth up to 25 m, depending on water turbidity and atmospheric conditions.

**Disadvantages**
- Relatively low accuracy & reliability
- Need water depth truth
Bathymetric Mapping using Multi-spectral Imagery

Physical principle

- When light passes through water, it becomes attenuated. Shallow water areas appear bright, and deep areas look dark on the image.
- Light attenuation and penetration is wavelength-dependent. Red band does not penetrate further than about 5 m in clear water, while blue band may penetrate clear water up to 25-30 m deep.

$k$: attenuation coefficient  
$\bar{z}$: water depth  
$L(\bar{z})$: downward irradiance at $\bar{z}$ m depth  
$L(0)$: downward irradiance at just below the water surface
Water Depth Algorithms

- **Multi-band Log-linear Algorithm**
  - 2 or more bands, most widely used inversion algorithm

General: 

\[ z = a_0 + a_1 X_1 + \cdots + a_n X_n \]
\[ X_i = \ln[R_w(\lambda_i) - R_\infty(\lambda_i)] \]
\[ i = 1, 2, \ldots, n \]

2 bands:

\[ z = \alpha_0 + \alpha_1 \ln[L(Blue) - L_\infty(Blue)] + \alpha_2 \ln[L(Green) - L_\infty(Green)] \]

- **Limitation**: 5 parameters, not good for low bottom albedo

- \( z \) : water depth
- \( n \) : the number of spectral bands
- \( R_w(\lambda_i) \) : observed radiance for band \( \lambda_i \) after atmospheric and sunglint corrections
- \( R_\infty(\lambda_i) \) : column radiance of optically deep water for band \( \lambda_i \)
- \( a_0, a_1, a_n \) : empirically determined coefficients (parameters)
Water Depth Algorithms

- **Non-linear Inversion Algorithm**
  - Stumpf et al. (2003)
  - \[ Z = m_1 \frac{\ln(nR_w(\lambda_i))}{\ln(nR_w(\lambda_j))} - m_0 \]

  \( m_0, m_1, \) and \( n \) are constant coefficients for the model
  \( R_w(\lambda_i) \) and \( R_w(\lambda_j) \): observed radiances (after atmospheric and sunglint corrections) for spectral bands \( i \) and \( j \).

  - Does not require subtraction of deep water, which expands the number of benthic habits over which it can be applied.
  - Has fewer empirical coefficients, more stable over broader area.

  - **Limitation:** non-linear, fitted manually in a trial-and-error fashions, time consuming, not true optimal.
Automated Optimization Method Based on Levenberg-Marquardt Algorithm

- A problem of nonlinear function minimization
- Merit function:

\[ \chi^2(m_0, m_1, n) = \sum_{k=1}^{K} (\hat{Z}_k - Z_k)^2 = \sum_{k=1}^{K} \left[ m_1 \frac{\ln(nL(\lambda_1)_k)}{\ln(nL(\lambda_2)_k)} - m_0 - Z_k \right]^2 \]

- Levenberg-Marquardt: elegant combination of Newton's method and the steepest descent method

\[
\begin{align*}
(1 + \lambda) \frac{\partial^2 \chi^2}{\partial m_0 \partial m_0} \Delta m_0 + \frac{\partial^2 \chi^2}{\partial m_1 \partial m_0} \Delta m_1 + \frac{\partial^2 \chi^2}{\partial n \partial m_0} \Delta n &= -\frac{\partial \chi^2}{\partial m_0} \\
\frac{\partial^2 \chi^2}{\partial m_0 \partial m_1} \Delta m_0 + (1 + \lambda) \frac{\partial^2 \chi^2}{\partial m_1 \partial m_1} \Delta m_1 + \frac{\partial^2 \chi^2}{\partial n \partial m_1} \Delta n &= -\frac{\partial \chi^2}{\partial m_1} \\
\frac{\partial^2 \chi^2}{\partial m_0 \partial n} \Delta m_0 + \frac{\partial^2 \chi^2}{\partial m_1 \partial n} \Delta m_1 + (1 + \lambda) \frac{\partial^2 \chi^2}{\partial n \partial n} \Delta n &= -\frac{\partial \chi^2}{\partial n} 
\end{align*}
\]

\( X_0 \): initial guest value
\( X \): minimum
Application Example – Moloka’i Island

Color composition of IKONOS blue, green and red bands
Application Example – Moloka‘i Island

<table>
<thead>
<tr>
<th>Iteration</th>
<th>$m_0$</th>
<th>$m_1$</th>
<th>$n$</th>
<th>$\chi^2$</th>
<th>$\frac{\Delta \chi^2}{\chi^2}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>41.073</td>
<td>35.006</td>
<td>111.172</td>
<td>11469.37</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>39.993</td>
<td>34.009</td>
<td>103.611</td>
<td>11348.46</td>
<td>1.05%</td>
</tr>
<tr>
<td>2</td>
<td>31.433</td>
<td>25.527</td>
<td>70.830</td>
<td>11039.59</td>
<td>2.72%</td>
</tr>
<tr>
<td>3</td>
<td>21.640</td>
<td>15.888</td>
<td>51.894</td>
<td>10572.00</td>
<td>4.24%</td>
</tr>
<tr>
<td>4</td>
<td>23.266</td>
<td>17.503</td>
<td>56.087</td>
<td>10056.19</td>
<td>4.88%</td>
</tr>
<tr>
<td>5</td>
<td>23.497</td>
<td>17.734</td>
<td>57.025</td>
<td>10030.76</td>
<td>0.25%</td>
</tr>
<tr>
<td>6</td>
<td>23.467</td>
<td>17.706</td>
<td>56.991</td>
<td>10030.71</td>
<td>0.0005%</td>
</tr>
</tbody>
</table>

Iterative fitting of optimal parameters for non-linear inversion model

Log-linear inversion model parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Best-fit</th>
<th>Std Error</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_0$</td>
<td>11.140</td>
<td>0.328</td>
<td>[10.484, 11.796]</td>
</tr>
<tr>
<td>$a_1$</td>
<td>10.976</td>
<td>0.116</td>
<td>[10.744, 11.208]</td>
</tr>
<tr>
<td>$a_2$</td>
<td>-5.845</td>
<td>0.136</td>
<td>[-6.117, -5.573]</td>
</tr>
</tbody>
</table>

RMSE of the estimated depths both models

<table>
<thead>
<tr>
<th>Depth (m)</th>
<th>0-5</th>
<th>5-10</th>
<th>10-15</th>
<th>15-20</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log-linear</td>
<td>1.34</td>
<td>2.01</td>
<td>1.65</td>
<td>3.00</td>
<td>2.10</td>
</tr>
<tr>
<td>Non-linear</td>
<td>2.07</td>
<td>2.17</td>
<td>1.63</td>
<td>2.87</td>
<td>2.20</td>
</tr>
</tbody>
</table>
Application Example – Moloka’i Island

![Diagram showing depth profiles and underwater topography of Moloka’i Island.]

- Depth (m) legend:
  - >20 m
  - 15-20 m
  - 10-15 m
  - 5-10 m
  - 0-1 m
  - 1-2 m

- Maps and profiles indicating different underwater structures:
  - Shore-normal Depth Profile
  - Shore-parallel Depth Profile

- Key features:
  - Reef flat
  - Reef crest
  - Fore reef
  - Reef base
  - Spur
  - Sand groove
Global Inversion Model

- Only one inversion equation is used for the entire image
- Multi-band method

\[ z = \alpha_0 + \alpha_1 \ln[L(Blue) - L_\infty(Blue)] + \alpha_2 \ln[L(Green) - L_\infty(Green)] \]

- Reality
  - heterogeneous bottom types and varying water quality

- Solution
  - geographically adaptive inversion model
Regional Models

- **Regional bathymetric inversion model**
  - Subdivide the image scene into several geographical regions
  - Fit and determine the model parameters using the water depth truth data tied to each geographical region

\[ z = \alpha_0 + \sum_{i=1}^{N} \alpha_i \ln[L(\lambda_i) - L_{\infty}(\lambda_i)] \]

\[ z = \alpha_0^j + \sum_{i=1}^{N} \alpha_i^j \ln[L(\lambda_i) - L_{\infty}(\lambda_i)] \quad (j=1, 2, ..., M) \]
Locally Adaptive Inversion Models

- Locally adaptive inversion models
  - One inversion equation for each local neighborhood:

\[
z = \alpha_0 + \sum_{i=1}^{N} \alpha_i \ln[L(\lambda_i) - L_\infty(\lambda_i)]
\]

\[
z = \alpha_0(x, y) + \sum_{i=1}^{N} \alpha_i(x, y) \ln[L(\lambda_i) - L_\infty(\lambda_i)]
\]

(x, y): geographical coordinates of the centroid point for each local area
Local neighborhood definition and weight determination

- Kernel regression method vs geographically weighted regression (GWR) method

Weighted Least-square Regression

\[ \hat{\alpha}(x, y) = \left[ X^T W X \right]^{-1} X^T W z \]

- Gaussian function vs bisquare function

Gaussian

\[ w_i = \exp \left( \frac{d_i^2}{b^2} \right) \]

Bi-square

\[ w_i = \left( 1 - \frac{d_i^2}{b^2} \right)^2 \text{ if } d_i < b; \]

\[ w_i = 0 \text{ otherwise.} \]
Case Study - Kaua’i Island, Hawaii
Results – global inversion model

\[ z = 27.17 + 4.40 \times \ln[L(Blue) - L_{\infty}(Blue)] - 10.17 \times \ln[L(Green) - L_{\infty}(Green)] \]

Global inversion model parameters

\[ r = 0.956 \]
Results – regional inversion model

\[ z = 23.99 + 0.52 \ln[L(Blue) - L_\infty(Blue)] - 4.21 \ln[L(Green) - L_\infty(Green)] \]

\[ z = 27.49 + 4.32 \ln[L(Blue) - L_\infty(Blue)] - 10.00 \ln[L(Green) - L_\infty(Green)] \]

\[ z = 24.41 + 3.88 \ln[L(Blue) - L_\infty(Blue)] - 9.07 \ln[L(Green) - L_\infty(Green)] \]

\[ z = 32.69 + 4.32 \ln[L(Blue) - L_\infty(Blue)] - 11.70 \ln[L(Green) - L_\infty(Green)] \]

Parameters of 4 regional models

\[ r = 0.974 \]
Results – local inversion model

$r = 0.995$
Comparison

RMSE of global, regional and local inversion models

<table>
<thead>
<tr>
<th>RMSE(m)</th>
<th>0-3m</th>
<th>3-6m</th>
<th>6-9m</th>
<th>9-12m</th>
<th>12-15m</th>
<th>15-18m</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global</td>
<td>1.35</td>
<td>1.04</td>
<td>1.19</td>
<td>1.29</td>
<td>1.62</td>
<td>1.92</td>
<td>1.43</td>
</tr>
<tr>
<td>Regional</td>
<td>1.26</td>
<td>0.87</td>
<td>0.88</td>
<td>1.15</td>
<td>1.19</td>
<td>1.23</td>
<td>1.11</td>
</tr>
<tr>
<td>Local</td>
<td>0.65</td>
<td>0.51</td>
<td>0.53</td>
<td>0.35</td>
<td>0.41</td>
<td>0.32</td>
<td>0.48</td>
</tr>
</tbody>
</table>
Bathymetry map from local inversion model

Bathymetric grid derived from IKONOS image using local inversion model
Conclusion

- The non-linear inversion model can produce slightly more accurate depth estimates for areas deeper than 10–15 m but slightly less accurate for very shallow areas.

- Geographically adaptive inversion models can effectively alleviate the spatial heterogeneity problem, without bottom type and water quality information.

- Geographically adaptive inversion models can give better and more consistent depth estimates than the conventional global inversion model.