Automated Subpixel Photobathymetry and Water Quality Mapping

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Abstract
New photobathymetry and water quality software is described here that utilizes subpixel analysis software (Subpixel Classifier) with an autonomous image calibration procedure and an analytic retrieval algorithm to simultaneously retrieve and report bottom depth and the concentrations of suspended chlorophyll, suspended sediments, and colored dissolved organic carbon on a per-pixel basis from four-band multispectral image data. From the derived composition, the QSC2 (Quantitative Shoreline Characterization, Version 2.0) software also computes and reports water column visibility parameters (vertical and horizontal subsurface sighting ranges and turbidity, each at four wavelength band passes, plus Secchi depth as a scalar) as well as depth and turbidity confidence. QSC2 compensates for the effects of the atmosphere, sun and sky reflections from the water surface, subpixel contributions from exposed land, and variations in the bottom material properties. All information is derived automatically from the pixel data alone. The performance of the QSC2 software was demonstrated using a four-band IKONOS image of Plymouth, Massachusetts. Accuracies of the image-derived compositions, water clarity, and depths were assessed using field and laboratory measurements for eight representative lakes in the scene. The means of the differences of the field-measured and image-derived suspended chlorophyll and colored dissolved organic carbon concentrations for the eight lakes were 1.82 μg/l and 4.34 mg/l, respectively. The image-derived concentrations of suspended sediments were all below the threshold of detection for the field samples (5 mg/l), in agreement with the field data. The mean of the differences between field-measured and image-derived Secchi depths was 0.76 m. The mean depth difference was 0.57 m.

Introduction
Retrieval of bottom depth, water composition, and water clarity information from satellite and airborne multispectral imagery has been attempted with mixed success, particularly for near-shore and inland lake waters. Attenuation of light by suspended and dissolved materials complicated past algorithms for retrieval of bottom depth. Most photobathymetry applications have either been for relatively clear waters, or characteristics of the water column were approximated using independently characterized pixels of nearby deep waters (Polcyn et al., 1970; Lyzenga, 1978; Lyzenga, 1981; Lyzenga, 1985; Clark et al., 1987; O’Neill and Miller, 1989; Philpot, 1989; Walker et al., 1996; Huguenin et al., 1997b; Zhang et al., 1999). Furthermore, the presence of reflected light from the bottom interferes with most empirical algorithms for retrieving the properties of the water column. Consequently, most water column characterization applications have been for optically deep waters (Gordon et al., 1988; Mausel et al., 1991; Garver and Siegel, 1997; O’Reilly et al., 1998; Carder et al., 1999; Dierssen and Smith, 2000; Reynolds et al., 2001; Ruddick et al., 2001; Cipollini et al., 2001; LaPotin et al., 2001; Maritorena et al., 2002).

Several factors affected past algorithm performance. These included incomplete model representations of bottom reflectance and water column optical attenuation characteristics; inadequate correction for surface reflections of sky radiance and sun glints; inadequate calibration for sun angle, atmospheric, and other environmental factors; and/or inadequate compensation for diverse and mixed bottom materials, among other factors. Attempting to compensate for these limitations, Lee et al. (2001) developed a semi-analytical model for shallow-water remote sensing using hyperspectral data and a model-driven optimization technique. They demonstrated that simultaneous retrieval of bottom depth and water column characteristics is indeed feasible for turbid shallow water cases. The simultaneously derived properties included bottom depth as a scalar, plus the spectra of bottom albedo, water absorption coefficients, and water backscattering coefficients. The spectra of water absorption coefficients and water backscattering coefficients were then fed into a model to derive the composition of the water column. Although accuracies of the retrieved parameters were not reported, the Lee et al. (2001) model was able to achieve reasonable agreement between retrieved depths and a NOAA chart and recent bathymetric survey. The retrieved chlorophyll concentrations were also in the range of a value measured at a nearby calibration site in their test image.

Although the Lee et al. (2001) model demonstrated that both bathymetric and water quality information can in principle be simultaneously retrieved from airborne spectral imagery, there is a need to be able to do this using commercially available multispectral sensors (e.g., IKONOS and Landsat Thematic Mapper). This is critical to meet data cost and availability (including historical coverage) requirements of water quality applications and to support rapid-response Naval operations requirements. Additional efficiency can also be gained if these retrievals can be achieved without the requirement for ground radiance measurements at calibration sites in the image, as required in the Lee et al. approach. This is critical for using archived and historical data, for supporting operations in denied or otherwise inaccessible areas, and for minimizing costs in water quality projects.

New photobathymetry and water quality software is described here that utilizes a different approach than that of...
Lee et al. (2001). The QSC2 (Quantitative Shoreline Characterization, Version 2.0) software simultaneously retrieves four scalar parameters (bottom depth, and the concentrations of suspended chlorophyll, suspended sediments, and colored dissolved organic carbon) on a per-pixel basis, requiring only four-band multispectral data, rather than hyperspectral data. From the retrieved composition, QSC2 computes and reports water column variability in surface measuring ranges and turbidity, each at four wavelength bands, plus Secchi depth as a scalar. It also performs an entirely autonomous calibration to reflectance, using only the image data, rather than requiring the use of MODTRAN (Moderate Resolution Transmittance Code, an atmospheric transmission and radiance calculation model and code developed by the Air Force Research Laboratory, Space Vehicles Directorate, Hanscom AFB, Massachusetts) and the collection of ground radiance measurements at calibration sites. The accuracy of these automatically derived water quality parameters was assessed using commercially available, four-band IKONOS data that were provided by Space Imaging, Inc. A region was selected in Plymouth, Massachusetts that contained sufficient variability in 1997a; Flanagan and Civco, 2001). It does this by identifying and removing unwanted spectral contributions from background materials in the pixels, and comparing the residual spectrum (after background removal) to a spectral signature for the material of interest. If the residual spectrum matches the signature spectrum (within an allowed tolerance), the pixel is designated as containing the material of interest. The process reports the fraction of the pixel containing the material (1.0 minus the fraction of background removed). QSC2 takes advantage of the background suppression capabilities of Subpixel Classifier to detect and isolate the spectral contribution of water in image pixels even when it occupies only a fraction of a pixel. QSC2 uses a different environmental correction process than the one in Subpixel Classifier, however. It uses instead Image Calibrator to automatically convert the detected water spectrum to units of apparent reflectance, utilizing image data alone and requiring no ground truth or external information (Huguenin et al., 1998). Subpixel Classifier’s interactive Signature Derivation module is also not used in QSC2. Instead, it uses a new automated process, described below, which was embedded within the Classification module. Finally, it adds a post-processing module, also described below, to simultaneously retrieve the water depth and water quality information.

**Approach**

A special version of Subpixel Classifier, referred to as QSC2, was created to simultaneously retrieve water depth and water quality information from image pixels. Subpixel Classifier (available as a module within ERDAS IMAGINE) is a multispectral/hyperspectral image processing software module that detects spectral contributions from materials of interest that may occupy only small fractions of image pixels (Huguenin et al., 1997a; Flanagan and Civco, 2001). It does this by identifying and removing unwanted spectral contributions from background materials in the pixels, and comparing the residual spectrum (after background removal) to a spectral signature for the material of interest. If the residual spectrum matches the signature spectrum (within an allowed tolerance), the pixel is designated as containing the material of interest. The process reports the fraction of the pixel containing the material (1.0 minus the fraction of background removed).

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**Automatic Signature Derivation**

The signature derivation process in QSC2 is a three-step process. The first step utilizes a standard unsupervised classifier, ISODATA clustering, to classify the image into eight primary spectral classes. This is followed by a “cluster busting” step, classifying each primary class into eight subclasses. The second step categorizes the class/subclass spectra into “water classes” and “non-water classes.” The eight primary class spectra and 64 subclass spectra are next converted to units of apparent reflectance using the output from Image Calibrator. Water classes/subclasses are then identified as those with reflectances (at λ > 0.75 μ) less than 0.1. The third step converts each water subclass spectrum (in original DN units) into a standard Subpixel Classifier signature using processes adapted from Subpixel Classifier’s Signature Derivation module. The water subclass spectrum serves as the signature spectrum, Sig(p,n), while randomly selected pixels from the subclass provide the necessary training data to establish the other two components of the Subpixel Classifier signature, namely, the spectral filters and intensity screen. Another signature, Sig(p,n), is derived from the mean of the water primary class spectra and randomly selected training pixels from the full set of water pixels.

**Water Detection**

The pixels, Ps(n), belonging to a particular water subclass, s, are processed to detect and isolate the water component, W(n), using the signature, Sig(s,n), for that sub-class only. Pixels belonging to the non-water subclasses are processed using Sig(p,n).

The background removal process is a modified version of the standard process in Subpixel Classifier. The modification restricts the candidate backgrounds to non-water backgrounds. Otherwise, it is the same as the standard process. Each pixel spectrum, P(n), is processed with the appropriate signature, Sig(s,n) for the water subclass pixels or Sig(p,n) for the non-water class pixels, to remove any subpixel non-water component (cloud or terrain), B(n), that may be present.

\[
W(n) = |P(n) - k, B(n)/(1 - k)| \tag{1}
\]

where W(n) is the detected water component of P(n) and k is the fraction of B(n) in P(n).

**Retrieval of Water Depth and Composition**

Central to the derivation of water depth and water quality information from the detected water spectrum, W(n), is a four-dimensional reflectance look-up table (LUT). Water reflectance in four spectral bands is predicted for sequences of 50 depths and 50 concentrations each of suspended minerals, suspended chlorophyll, and dissolved organic carbon using the expression

\[
R(n) = w(n)F(n)[n/(d(n))|^1 - e^{-2z(n)} + w(n)F(n)\ e^{-2z(n)}] \tag{2}
\]

Here, R(n) is the reflectance of W(n), exclusive of glint. The right hand side of Equation 2 represents the sum of the volume reflectance (first term), Rvol(n), and bottom reflectance (second term), Rbot(n), contributions to R(n). The w(n) term is the effective two-way air-water interface attenuation. F(n) is a proportionality factor between the volume reflectance of the water column below the air-water interface and the ratio b(n)/a(n), where a(n) and b(n) are the absorption and backscattering coefficients, respectively, of the water column. The r(n) term represents the bottom reflectance, while 2z(n) is the effective two-path water column total attenuation coefficient, where c(n) = a(n) + b(n), and z is depth. To populate the LUT, the product w(n)F(n) was assigned a wavelength invariant value of w(n)F(n) = 0.1735. The basis for this is as follows.

The w(n) term can be defined by the expression (Smith and Baker, 1986; Mueller et al., 1995)

\[
w(n) = t(n) \* [1 - p(n,θ)]/n(1) \tag{3}
\]

Here t(n) is the transmittance of the downwelling irradiance across the air-sea interface, estimated to be 0.96 at visible wavelengths (Smith and Baker, 1986; Dierssen and Smith, 1997). The Fresnel reflectance from water to air, r(θ,θ), has been estimated to be 0.021 to 0.022 over the visible wavelength range (Dierssen and Smith, 2000). Using the standard index of refraction for water, n(θ), and the air-water index, 1.0, an effective two-way path length is calculated and the result is used to calculate the ratio 2z(n) = 2z(n)/n(1)
with conclusions and values derived from independent methodologies (Dierssen and Smith, 2000). 

\( F(n) \) in \( w(n)F(n) \) includes the following: a factor \( f(n) \) that relates apparent (measured) reflectance to inherent reflectance of the water column (Morel and Gentili, 1993); a factor \( Q(n) \) that describes the anisotropy of the radiance distribution, \( Q(n) = E(n)/E_L(n) \), where \( E_L \) is upwelling irradiance and \( E \) is the corresponding upwelling radiance (Morel and Gentili, 1991; Morel and Gentili, 1993); and sun angle effects. Although there are wavelength dependencies in the constituent terms, \( F(n) \) was found to be relatively invariant with respect to wavelength (Morel and Gentili, 1991; Morel and Gentili, 1993; Bukata et al., 1995, pp. 92–102). There is some dependence of \( F(n) \) on the magnitude of \( b(n)/a(n) \) and solar incidence angle, however (Bukata et al., 1995, pp. 92–102). Following the formalism of Gordon et al. (1975) for open ocean waters, Kirk (1984) performed Monte Carlo simulations to estimate \( F(n) \) for more turbid waters, from which

\[
F(n) = 0.975 - 0.629\mu_4 \tag{4}
\]

where \( \mu_4 = \cos(\theta_s) \), \( \theta_s \) being the refracted solar incident angle. Jerome et al. (1983) noted a second-order dependence of \( F(n) \) on the backscattering probability, \( b(n) \). Kirk (1991) investigated this further, leading to an expression for \( F(n) \) dependent on both \( \beta\) and \( \mu_4 \) (Bukata et al., 1995, p. 101). Other expressions were developed by D'Foor (1978) to address the complex scattering properties of turbid estuarine waters at low sun angles, leading to an expression that takes into account additional dependencies on sun angle. These latter effects, however, can generally be ignored for all but low sun angles. The Monte Carlo simulations were carried out at depth \( z = 0 \), i.e., just below the air/surface interface. \( F(n) \) can be assumed to be invariant with depth as long as the water column is homogeneous. Using refracted solar incident angles representative of most commercially available sensor data, and neglecting the weak dependence on wavelength, \( w(n)F(n) = 0.1735 \) becomes a reasonable approximation.

The bottom reflectance term, \( w(n)r(n) \), in Equation 2 has a default value that was derived empirically from a shallow-water IKONOS image of the Bahamas (where the water is nearly pure from an optical perspective). Errors in assumed \( w(n) \) are at least partially compensated for by an empirical correction factor, \( \gamma(s,n) \), described below. The user can optionally input alternative \( r(n) \), or \( w(n)r(n) \) can be derived from the image being processed.

\[
a(n) = a_{aw}(n) + C_{CSMaSM}b_{aw}(n) + C_{CSMb}b_{aw}(n) + C_{CSMc}b_{aw}(n) + C_{CSMd}b_{aw}(n) \tag{5}
\]

and

\[
b(n) = b_{aw}(n)\beta(n) + C_{CSMaSM}(n)b_{aw}(n)\beta(n) + C_{CSMb}(n)b_{aw}(n)\beta(n). \tag{6}
\]

In these expressions, \( a_{aw}(n) \) and \( b_{aw}(n) \) are the absorption and backscattering cross-section spectra, respectively, of pure water. The other terms, \( a(n) \) and \( b(n) \), are the known absorption and backscattering cross-section spectra, respectively, of other aquatic components suspected to be in the water column. Note that the backscattering cross section for each component is explicitly expressed as the product of the scattering cross section, \( b(n) \), and backscattering probability, \( \beta(n) \), for that component. \( C_{CSMaSM}, C_{CSMb}, \) and \( C_{CSMc} \) are the concentrations of suspended chlorophyll, suspended minerals, and chromophoric dissolved organic carbon, respectively. Numerous suspended and dissolved constituents can exist within the water column, and the chemistry can be quite complex. However, not all of the constituents are optically significant. Typically, only a few components affect the volume reflectance of a water mass even under complex chemistry conditions (c.f., Bukata et al., 1981). From an optical point of view, the water mass can be considered a combination of pure water, a suspended organic component, a dissolved organic component, and a suspended inorganic component. For most waters, the optically dominant suspended organic component is chlorophyll (in the form of chlorophyll + phaeophytin). The optically dominant suspended inorganic component is typically in the form of suspended minerals. The optically dominant dissolved organic matter component is the melanoid-colored fraction, i.e., the fraction produced by the Maillard reaction (Kalle, 1966), typically amounting to about 10 to 40 percent of the total dissolved organic matter concentration (Bukata et al., 1995, p. 123). Although this may be an over-simplification of the state of the water body, this four-component optical model is generally sufficient to describe the volume reflectance characteristics of most inland and coastal waters (c.f., Bukata et al., 1981; Bukata et al., 1995, p. 105).

The effective two-path water column total attenuation coefficient, \( jc(n) \), is approximated using \( j = 2 \) in Equation 2. The \( j \) term is highly complex, but it can be approximated by

\[
J = \{1/(\cos(\theta_s)) + |D_{p}^n|/\cos(\theta_s)\} \tag{Lee et al., 1999, where \( \theta_s \) and \( \theta_i \) are the subsurface solar zenith angle and subsurface viewing angle from nadir, respectively; \( D_{p}^n = 1.04[1 + 5.4u(n)]^{10}\); \( u(n) = b(n)/[a(n) + b(n)]; \) and \( a(n) \) and \( b(n) \) are the absorption and backscattering coefficients, respectively, of the water column. For most water compositions and viewing geometries, \( j = 2 \), which is also consistent with the assumption of Walker et al. (1990).

Equations 2, 5, and 6 served as the governing equations for populating the LUT using the various combinations of \( z, C_{CSMaSM}, C_{CSMb}, \) and \( C_{CSMc} \). To simultaneously retrieve these four parameters from the detected water spectra, \( W(n) \), an additional factor, \( \gamma(s,n) \), is needed. Because \( w(n)r(n) \), \( w(n)F(n) \), glint contributions, and other properties controlling \( W(n) \) can be different from those in the LUT, an empirical correction is autonomically derived to partially compensate for these combined differences. For each water subclass signature, \( \gamma(s,n), \) a signature-specific spectrum, \( \text{SUNLUT}(s,n) \), is derived: i.e.,

\[
\text{SUNLUT}(s,n) = \text{SUNFACTOR}(n) \ast \gamma(s,n). \tag{7}
\]

\( \text{SUNLUT}(s,n) \) is then used in place of \( \text{SUNFACTOR}(n) \) from Image Calibrator to convert detected water spectra to reflectance for use with the LUT: i.e.,

\[
R_{\text{LUT}}(s,n) = [W(s,n) - \text{ARAD}(n)]/SUNLUT(s,n). \tag{8}
\]

To derive \( \text{SUNLUT}(s,n) \), \( \text{SIG}(s,n) \) for class \( s \) is first converted to reflectance using the two environmental correction spectra from Image Calibrator:

\[
R(s,n) = [(\text{SIG}(s,n) - \text{ARAD}(n))/\text{SUNFACTOR}(n)] - \text{Psurf} \tag{9}
\]

For each \( R(s,n) \), the composition and depth is derived from the LUT; and the actual LUT reflectance, \( R_{\text{LUT}}(s,n) \), for that depth and composition is retrieved from the LUT. The ratio of \( R_{\text{LUT}}(s,n) \) to \( R(s,n) \) then defines \( \gamma(s,n) \) in Equation 7. The \( \text{Psurf} \) term is explicitly determined and removed from bands based on the reflectance values for bands with center wavelengths longer than 0.75 \( \mu m \), when available (e.g., Landsat Thematic Mapper). Otherwise, it is implicitly removed through use of \( \gamma(s,n) \) with the discrete LUT.

**Water Clarity Characterization**

Once \( a(n) \) and \( b(n) \) are known, additional water clarity information is derived and reported for each water detection. This includes the vertical and horizontal subsurface sighting ranges

\[
\text{VSSR}(n) = 4.605/[1.4a(n) + 0.03b'(n)]. \tag{10}
\]
and

\[
HSSR(n) = 4.605/([a(n) + b'(n)]). \tag{11}
\]

Subsurface sighting range is defined here as the distance over which reflected radiance is attenuated to 0.01 of its starting value. Equation 10 is based on the Beer’s Law expression for attenuation of irradiance, \(E(n,z) = E(n,0)\exp(-k(n)z)\), for \(E(n,z)/E(n,0) = 0.01\) and a vertical attenuation coefficient of \(k(n) = 1.4a(n) + 0.03b'(n)\) (Pickard and Emery, 1982, p. 104), with \(b'(n)\) being the scattering coefficient, not the backscattering coefficient. Equation 11 is based on the same Beer’s Law expression, but substituting the total attenuation coefficient, i.e., \(c(n) = a(n) + b'(n)\), for the vertical attenuation coefficient (Pickard and Emery, 1982, p. 104).

\(VSSR(n)\) is directly analogous to the traditional field-measured Secchi depth parameter. Secchi depth represents the depth at which a submerged disk, viewed from above the air-water interface, loses contrast with the background. Like \(VSSR(n)\), Secchi depth generally corresponds to the depth where \(E(n,z)/E(n,0) = 0.01\) (Bukata et al., 1988). The principal distinction between the two is the position of the observer: \(VSSR(n)\) is from a vantage point below the air-water interface, while Secchi depth is measured from above. Secchi depth can be estimated from the total attenuation coefficient reported by QSC2. Bukata et al. (1988) derived empirical relationships between Secchi depth (\(S\)) and total attenuation coefficient (\(c = \text{total attenuation coefficient integrated over the visible wavelength range}\) for several bodies of water (five of the Great Lakes) covering the range 0.5 m \(\leq S \leq 20\) m. The results took the form of \(c = AS^{-0.92}\), where \(A\) and \(B\) were constants derived from regression analyses. There were differences between lakes, with \(A\) ranging from 2.05 to 3.85 and \(B\) ranging from 0.8 to 1.0. Correlation coefficients were high, however (0.98 to 0.99). Using the means of \(A\) and \(B\) for the five lakes, and transforming the expression into \(S\) as a function of \(c\), one can obtain the following first-order estimate for Secchi depth:

\[
S = (4.30/c)^{0.98}. \tag{12}
\]

Here \(c\) is the mean of \(c(n)\) across the visible wavelength range. Comparison of Equations 11 and 12 with \(c(n) = a(n) + b'(n)\) reveal that Secchi depth is generally comparable in magnitude to \(HSSR(n)\) over the visible wavelength range: \(S = 0.928\ \text{HSSR}^{0.98}\). Note that the field-measured Secchi depth is a qualitative parameter, dependent on the perception and experience of the observer. Also, because it involves lowering a disk into the water, it can only be measured in the field when Secchi depth is less than actual depth. In contrast, \(S\) from Equation 12 is quantitatively derived from the three image-derived concentrations, and it is therefore not as qualitative and it is not restricted to depths less than the actual depth.

Another water clarity parameter reported by the software is turbidity. Generally, turbidity refers to the amount of attenuation by particulate scattering in the water, usually expressed in Nephelometric Turbidity Units (NTU). However, there is not a universally accepted quantitative relationship between the concentration of particulates and NTU units. The off-axis NTU measurement geometry utilizes particulate scattering in a way that includes attenuation by both absorption and scattering when particulates are present, but it reports below-threshold attenuation when particles are not present. Because of the inclusion of the effects of absorption in the attenuation measurement, the NTU units cannot be used to derive particle concentration. As an alternative to NTU, one can instead use the definition of turbidity adopted by Pickard and Emery (1982, p.104), namely, turbidity = total attenuation coefficient, \(c(n)\). The QSC2 software reports turbidity as \(c(n)\) rather than NTU. NTU and \(c(n)\) are comparable indicators of water clarity when particulates are present. Because of the difference in measurement geometry, however, \(c(n)\) values may not be good indicators of turbidity when particulate concentrations are low, e.g., in low-particulate waters containing appreciable concentrations of colored dissolved organic carbon (CDOM).

In addition, turbidity confidence and depth confidence values are reported for each pixel, providing a means for identifying compositional, visibility, and depth errors caused by uncompensated errors in the model assumptions. The accuracies of the reported depth and water quality parameters can vary from pixel to pixel due to a variety of factors. These can include uncompensated differences in bottom materials, surface reflectance, etc. They can also include anomalous materials in the water column. Turbidity confidence is

\[
C_T = 1 - f\]

where \(f\) is the least-squares fit value between \(R_{LTU}(s,n)\) and \(R(s,n)\). Depth Confidence is

\[
C_D = 1 - f \text{ for } 0.25 \text{ m} \leq z \leq 1.5^*S\]

\[
= 0 \text{ for } z < 0.25 \text{ m, or } z > 1.5^*S \tag{14}
\]

where \(S\) is the image-derived Secchi depth, defined by Equation 12. The two limits in Equation 14 reflect a problem inherent in the LUT approach, namely, the potential for multiple solutions. The problem is most acute when the bottom does not contribute to pixel reflectance, i.e., when \(z\) is greater than 1.5\(^*\)S. When this occurs, \(z\) is frequently reported as anomalously shallow (\(z\) less than 0.25 m); hence, the two limits in Equation 14. The multiple solution problem can potentially manifest itself in one or more of the derived parameters other than depth. In that case, the correct solution can be assumed to be the one closest to the signature’s derived parameter values.

**QSC2 Accuracy Assessment**

The accuracy of QSC2 was assessed using an Ikonos image and field sample data for a portion of Plymouth harbor and a set of nearby inland lakes in southeastern Massachusetts. The image, acquired on 30 August 2001 as part of GeoSyntec Consultant’s NASA funded ARC Project with Brown University, was a four-band multispectral product with 4-m GSD pixels, resampled in nearest-neighbor format. The image is shown in Plate 1.

**Ground Truth Field Data**

Field data were acquired at sites in numerous inland lakes in the image to assess the accuracy of the image-derived results. The locations and names of the lakes in which field samples were acquired are shown in Plate 1. Field data and samples were acquired from canoes by qualified GeoSyntec field staff on several dates between June and August, 2001. The date, time, location (GPS UTM coordinates), and local weather conditions for each in situ measurement and water sample collection were recorded. Field data included in situ measurements of water temperature, turbidity (Nephelometric Turbidity Units), Secchi depth (meters), actual depth (meters), specific conductivity (micromhos/cm), dissolved oxygen (mg/l), pH, and Oxygen Reduction Potential (mV). Water samples were collected near the surface and analyzed in the laboratory by Alpha Analytical Labs of Westborough, Massachusetts at the direction of GeoSyntec. Laboratory analyses included measurements of total phosphorous (mg/l), Chlorophyll a (µg/l), turbidity (NTU), dissolved organic carbon (mg/C/l), total suspended solids (mg/l), and NO\textsubscript{3}/NO\textsubscript{2} (mg/l).

The sampling stations were identified using the DGPS coordinates recorded at the field sites. The image was projected into the UTM WGS-84 projection, and the accuracy of pixel locations was estimated to be within 12 m (horizontal). Because
of the locational uncertainty, field-measured depths and water quality data were compared to the mean image-derived values for 3- by 3-pixel clusters, centered on the registered location.

**Depth**
The image-derived depths for the various water bodies in the image are illustrated in Plate 2a. In Plate 2b, the depths for the harbor area are compared to a USGS topographic map for the same area (depth in feet). The image-derived depths in the harbor are in good general agreement with the depths on the map, but there is significantly more detail in the image map not available from the topographic map or the corresponding nautical chart (not shown). A comparison of image-derived depths to field-measured depths is presented in Table 1 for eight representative inland lakes. All image-derived depths are included in the plates and table, although only three of the eight representative inland lakes. All image-derived depths to field-measured depths is presented in Table 1 for eight representative inland lakes. All image-derived depths are included in the plates and table, although only three of the depths in the table passed the valid-depth filter (0.25 m < depth < 1.5 m).

Differences between the field-measured and image-derived depths for the three valid measurements ranged from 0.03 m to 1.29 m, with a mean of 0.57 m. A comparison of the field-measured Secchi depths in Table 1 to field-measured Secchi depths reveal that the actual depths were less than 1.5 times the field-measured Secchi depths for only two of the three "valid" stations ("Muddy" and "Lwest"). The bottom would only have been visible at these latter two stations. Depths were underestimated by 0.03 m and 0.38 m, respectively, yielding a mean error of 0.21 m at these locations. At the third site ("Bwest"), actual depth was more than twice the field-measured Secchi depth, while the image-derived depth was very close to the image-derived Secchi depth, erroneously allowing it to pass the filter. The field-measured depths at the other five sample stations were all greater than 1.5 times the field-measured Secchi depth, and they were thus correctly identified as having invalid depths.

**Water Composition**
Plate 3 presents the concentrations of suspended chlorophyll (left), suspended sediments (center), and colored dissolved organic matter (right). Comparison of the patterns of derived concentrations in Plate 3 with depth (Plates 2a and 2b) reveals little or no evidence of any unwanted depth dependencies of the concentrations.

**Suspended Chlorophyll**
Quantitative comparisons of the image-derived concentrations with the field-measured concentrations for the same lake sites listed in Table 1 are presented in Tables 2, 3, and 4. Table 2 illustrates the concentrations of suspended chlorophyll a for the same sites listed in Table 1. The mean of the differences between the image-derived and field-measured chlorophyll concentrations for the complete set of eight sample stations is 1.82 µg/l. In contrast, the mean difference for the three sample stations having valid depths ("Muddy," "Lwest," and "Bwest") is 1.23 µg/l while, for the two samples actually having a visible bottom ("Muddy" and "Lwest"), it is 0.70 µg/l. This suggests that the image-derived concentrations of suspended chlorophyll may potentially have been adversely affected by the errors in depth calculation for the cases in which the bottom is not visible. However, other factors may have also contributed.

First, the water sample represents a small volume (≤ 1 liter) that may not be representative of the much larger volume represented by the 3- by 3-pixel (144 m²) area mean. This is particularly true if the water body is horizontally and/or vertically heterogeneous. Also complicating the assessment of accuracy is the fact that the dates of field sampling did not coincide with the date of image acquisition. Chlorophyll concentration in lakes not only varies with season but can also vary with changes in temperature, hours of sunlight, and nutrient levels. An example of this can be observed at the Billington Sea sampling station. This location was sampled on six dates (26 June 2001, 12 July 2001, 28 July 2001, 13 August 2001, 22 August 2001, and 29 August 2001), during which period the sampled chlorophyll a concentrations progressively increased from 5.12 to 37.20 µg/l. The corresponding image-derived values at these five Billington Sea sampling stations, all measured simultaneously from the Ikonos imagery on 30 July 2001, revealed much less variation, ranging from 13.39 to 17.78 µg/l with a mean of 16.07 µg/l. This suggests that the variations in the Billington Sea field samples were more temporal than spatial. The differences in Table 2 could thus also be due in part to temporal differences in chlorophyll concentration between the dates of sampling and image acquisition (30 July 2001).

**Suspended Minerals**
The image-derived concentrations of suspended sediments are listed in Table 3 for the same eight sample locations as in

<table>
<thead>
<tr>
<th>Station</th>
<th>Date</th>
<th>Image-Derived</th>
<th>Field-Measured</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stri</td>
<td>26 Jun 01</td>
<td>(5.41)</td>
<td>5.00</td>
<td>n/a</td>
</tr>
<tr>
<td>Smelt</td>
<td>22 Aug 01</td>
<td>(7.64)</td>
<td>4.80</td>
<td>n/a</td>
</tr>
<tr>
<td>Muddy</td>
<td>29 Aug 01</td>
<td>4.97</td>
<td>5.00</td>
<td>-0.03</td>
</tr>
<tr>
<td>Micajah</td>
<td>28 Jul 01</td>
<td>8.89</td>
<td>8.00</td>
<td>n/a</td>
</tr>
<tr>
<td>Lwest</td>
<td>28 Jul 01</td>
<td>4.02</td>
<td>4.50</td>
<td>-0.48</td>
</tr>
<tr>
<td>Cooks</td>
<td>22 Aug 01</td>
<td>3.34</td>
<td>3.80</td>
<td>n/a</td>
</tr>
<tr>
<td>Bwest</td>
<td>28 Jul 01</td>
<td>2.51</td>
<td>3.80</td>
<td>-1.29</td>
</tr>
<tr>
<td>BillSea</td>
<td>13 Aug 01</td>
<td>(0.16)</td>
<td>2.30</td>
<td>n/a</td>
</tr>
</tbody>
</table>

**Table 2. Comparison of Image-Derived and Field-Measured Concentrations of Suspended Chlorophyll a (µg/l) at Sampled Inland Lake Locations in the Plymouth Harbor Image**

<table>
<thead>
<tr>
<th>Station</th>
<th>Date</th>
<th>Image-Derived</th>
<th>Field-Measured</th>
<th>Difference</th>
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<tbody>
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<td>1.14</td>
<td>-0.44</td>
</tr>
<tr>
<td>Smelt</td>
<td>22 Aug 01</td>
<td>5.84</td>
<td>1.90</td>
<td>+3.94</td>
</tr>
<tr>
<td>Muddy</td>
<td>29 Aug 01</td>
<td>1.59</td>
<td>0.99</td>
<td>+0.60</td>
</tr>
<tr>
<td>Micajah</td>
<td>28 Jul 01</td>
<td>1.04</td>
<td>2.90</td>
<td>-1.86</td>
</tr>
<tr>
<td>Lwest</td>
<td>28 Jul 01</td>
<td>2.04</td>
<td>2.7</td>
<td>-0.66</td>
</tr>
<tr>
<td>Cooks</td>
<td>22 Aug 01</td>
<td>0.96</td>
<td>1.17</td>
<td>-0.21</td>
</tr>
<tr>
<td>Bwest</td>
<td>28 Jul 01</td>
<td>6.61</td>
<td>4.30</td>
<td>+2.31</td>
</tr>
<tr>
<td>BillSea</td>
<td>13 Aug 01</td>
<td>16.63</td>
<td>12.20</td>
<td>+4.43</td>
</tr>
</tbody>
</table>

**Table 3. Comparison of Image-Derived Suspended Sediments (mg/l) and Field-Measured Total Suspended Solids (mg/l) Concentrations at Sampled Inland Lake Locations in the Plymouth Harbor Image [5 mg/l Detection Limit, ND (Not Detect), and NS (Not Sampled)]**

<table>
<thead>
<tr>
<th>Station</th>
<th>Date</th>
<th>Image-Derived</th>
<th>Field-Measured</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stri</td>
<td>26 Jun 01</td>
<td>5.10</td>
<td>ND</td>
</tr>
<tr>
<td>Smelt</td>
<td>22 Aug 01</td>
<td>2.47</td>
<td>ND</td>
</tr>
<tr>
<td>Muddy</td>
<td>29 Aug 01</td>
<td>2.19</td>
<td>ND</td>
</tr>
<tr>
<td>Micajah</td>
<td>28 Jul 01</td>
<td>1.69</td>
<td>NS</td>
</tr>
<tr>
<td>Lwest</td>
<td>29 Aug 01</td>
<td>1.77</td>
<td>ND</td>
</tr>
<tr>
<td>Cooks</td>
<td>29 Aug 01</td>
<td>3.22</td>
<td>ND</td>
</tr>
<tr>
<td>Bwest</td>
<td>28 Jul 01</td>
<td>2.41</td>
<td>NS</td>
</tr>
<tr>
<td>BillSea</td>
<td>22 Aug 01</td>
<td>2.78</td>
<td>ND</td>
</tr>
</tbody>
</table>
Tables 1 and 2. TSS was measured by traditional gravimetric analysis for only four of the samples in Table 3. Sediment concentrations for each of four samples were below the detection threshold (5 mg/l). Of the 15 total field samples analyzed for TSS (only four of which are included in Table 3), only one yielded a value at the detection threshold. That sample, drawn from the Billington Sea on 29 August 2001, yielded a field-derived value of 5 mg/l, which was close to the detection threshold (5 mg/l). Of the 15 total field samples analyzed from sample filtrates, using a 0.45-μm filter, that were analyzed, the image-derived concentrations were in each case significantly below the 5 mg/l detection threshold, contrasting with the non detect (ND) reports for these samples.

**Dissolved Organic Carbon**

Table 4 reflects the image-derived concentrations of colored dissolved organic carbon (CDOM) as compared to the field-measured concentrations of dissolved organic carbon (DOC). The two concentrations are not directly comparable; therefore, comparison of the two concentrations has to be done with considerable caution. The field-measured concentrations are from sample filtrates, using a 0.45-μm filter, that were analyzed for dissolved organic carbon using a high-temperature combustion analysis procedure. In contrast, the image-derived CDOM concentrations represent the concentration of carbon in the yellow and brown melanoid portion of the dissolved organic matter, i.e., the colored fraction produced by the Maillard reaction.

Note that the image-derived values in Table 4 are consistently higher than the field-measured values. The mean of the differences for the eight sample stations is 4.34 mgC/l, which is comparable to the mean of the differences for the three sites having valid depths (5.0 mgC/l). This suggests that the image-derived concentrations of CDOM were probably not noticeably affected by any bottom contribution to pixel radiance.

The origin of the differences between the field sample and image-derived concentrations is uncertain. One possibility is that the differences are due to the differences in sampling characteristics. The field samples were collected near the surface, while the image-derived values are vertically integrated to depths of 1.2 to 6 m, depending on the Secchi depth. In the absence of significant circulation and mixing, dissolved organic matter can potentially develop vertical concentration gradients that could either enhance or depress concentrations near the surface relative to the vertically integrated column concentrations. In areas of high primary production, for example, a major source of dissolved organic carbon is production by algae degradation (autochthonic DOC). Because photosynthetic algae tend to be more concentrated near the surface, concentrations of dissolved organic matter in areas of high primary production can be enhanced near the surface. Conversely, in areas of low primary production, dissolved organic carbon concentrations can be suppressed near the surface as a result of egesta assimilation by the algae (Bukata et al., 1995, p. 123). The chlorophyll concentrations in Table 2 are generally low in all but the Billington Sea sample. This suggests the possibility that, at most of the sample stations, primary production may also have been low, and, consequently, that surface DOC concentrations (where the sampling occurred) may have been suppressed relative to the vertically integrated column concentrations. This could also have been true at the Billington Sea site, in spite of the relatively high concentrations of chlorophyll there.

**Water Clarity**

QS2 reported four indicators of water clarity, derived from the retrieved composition. VSSR(n) and HSSR(n) were reported for four wavelength ranges corresponding to the Ikonos sensor band passes for Band 1 (445 to 516 nm), Band 2 (506 to 595 nm), Band 3 (632 to 698 nm), and Band 4 (757 to 853 nm). The other two reported water clarity parameters included turbidity (total attenuation) for the same four band passes and an estimate of Secchi depth.

<table>
<thead>
<tr>
<th>Station</th>
<th>Date</th>
<th>Image-Derived</th>
<th>Field-Measured</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stri</td>
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<td>6.39</td>
<td>3.80</td>
<td>2.59</td>
</tr>
<tr>
<td>Smelt</td>
<td>22 Aug 01</td>
<td>7.29</td>
<td>3.00</td>
<td>4.29</td>
</tr>
<tr>
<td>Muddy</td>
<td>29 Aug 01</td>
<td>8.80</td>
<td>3.00</td>
<td>5.80</td>
</tr>
<tr>
<td>Micajah</td>
<td>28 Jul 01</td>
<td>5.72</td>
<td>1.50</td>
<td>4.22</td>
</tr>
<tr>
<td>Lwest</td>
<td>28 Jul 01</td>
<td>7.78</td>
<td>3.70</td>
<td>4.08</td>
</tr>
<tr>
<td>Cooks</td>
<td>22 Aug 01</td>
<td>7.89</td>
<td>2.90</td>
<td>4.99</td>
</tr>
<tr>
<td>Bwest</td>
<td>28 Jul 01</td>
<td>8.62</td>
<td>3.70</td>
<td>4.92</td>
</tr>
<tr>
<td>BillSea</td>
<td>13 Aug 01</td>
<td>7.24</td>
<td>3.60</td>
<td>3.64</td>
</tr>
</tbody>
</table>

Plate 4 (left) shows the Vertical Subsurface Sighting Range (VSSR(n)) output plane for the Band 1 band pass. Output planes for the Bands 2, 3, and 4 band passes are not shown in this table. This is because VSSR(n) for the Bands 1, 2, and 3 band passes have very similar patterns to the output plane in Plate 4, differing only in magnitude. The VSSR(n) output plane for the Band 4 band pass is not shown because the spatial variation is smaller than the bin size (1.2 to 1.5 m) and it has no visible structure. The VSSR(n) ranges do differ across the various band pass ranges, however, as seen in the histograms for the various bands in Plate 4 (right).
The patterns in the VSSR\(_n\) output plane in Plate 4 represent variations in water clarity due to variations in the concentrations of the suspended chlorophyll, suspended sediments, and/or colored dissolved organic carbon in the pixel water column. Comparisons to the compositional maps in Plate 3 can be used to determine which constituents are primarily responsible for the variations in water clarity at any location of interest in the image.

Examination of the histograms in Plate 4 reveals that VSSR\(_n\) generally decreased with increasing wavelength. This reflects a progressive increase in light attenuation toward the longer wavelengths, which is consistent for waters containing low to moderate concentrations of suspended chlorophyll, dissolved organic carbon, and suspended sediments. There is also a generally progressive decrease in the spread of histogram values in Plate 4 with increasing wavelength. The
sample stations included in the previous tables. The differences between the image-derived and field-measured values are also included. With the exception of Micajah Pond, the image-derived and field-measured Secchi depths agree to within a meter. Indeed, the mean of the differences for the eight sample stations is 0.76 m. This is comparable to the mean of the differences for the three sites having valid depths (0.70 m), suggesting that the image-derived Secchi depths were probably not noticeably affected by bottom contribution to pixel radiance.

The reason for this spread can be seen in Figure 1, where the mean of VSSR(n) for the four band passes is plotted separately for an area containing only the harbor and an area containing only the inland lakes. The two VSSR(n) plots reflect two very different compositional characteristics for the harbor and inland lakes, progressively converging with increase in wavelength. The histograms in Plate 4 are for the image as a whole, and the spread in values reflect the divergence for the two classes of water seen in Figure 1.

HSSR(n)
Plate 5a (left) presents the Horizontal Subsurface Sighting Range output plane for the Band 1 band pass. The histograms for the Bands 1 through 4 band passes are shown on the right. Note that the patterns are generally similar to those in the VSSR(n) output plane in Plate 4. HSSR(n) is less than VSSR(n) due primarily to the increased contribution from optical scattering by suspended materials in HSSR(n) (Equation 10 versus 11). Like VSSR(n), the sequence of image-mean HSSR(n) over the four band passes for the harbor is different from that of the lakes, showing a progressive convergence with increasing wavelength. This can be seen in Figure 1, where image-mean HSSR(n) for the four band passes is plotted for the harbor and inland lakes areas.

Turbidity
In Plate 5b, turbidity is shown in the output plane for the Band 1 band pass. The histograms for the Bands 1 through 4 band passes are shown on the right. Note that the patterns are generally similar to those in the VSSR(n) and HSSR(n) output planes in Plates 4 and 5b, respectively.

Secchi Depth
In Table 5 the image-derived Secchi depths are compared to the field-measured Secchi depths for the same eight field sample stations included in the previous tables. The differences between the image-derived and field-measured values were also included. With the exception of Micajah Pond, the image-derived and field-measured Secchi depths agree to within a meter. Indeed, the mean of the differences for the eight sample stations is 0.76 m. This is comparable to the mean of the differences for the three sites having valid depths (0.70 m), suggesting that the image-derived Secchi depths were probably not noticeably affected by bottom contribution to pixel radiance.

The origin of the differences between the image-derived and field-measured Secchi depths in Table 5 is uncertain, but it appears to be due at least in part to the differences between the two measurement approaches. Field-measured Secchi depth is a subjective parameter that depends on the overhead radiance characteristics, surface roughness, contrast of the Secchi disk against the background, and experience of the

<table>
<thead>
<tr>
<th>Station</th>
<th>Date</th>
<th>Image-Derived</th>
<th>Field-Measured</th>
<th>Difference</th>
</tr>
</thead>
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<td>3.0</td>
<td>-1.0</td>
</tr>
<tr>
<td>Smelt</td>
<td>22 Aug 01</td>
<td>2.7</td>
<td>3.5</td>
<td>-0.8</td>
</tr>
<tr>
<td>Muddy</td>
<td>29 Aug 01</td>
<td>3.5</td>
<td>4.5</td>
<td>-1.0</td>
</tr>
<tr>
<td>Micajah</td>
<td>28 Jul 01</td>
<td>4.6</td>
<td>6.0</td>
<td>-1.5</td>
</tr>
<tr>
<td>Loest</td>
<td>28 Jul 01</td>
<td>3.8</td>
<td>3.2</td>
<td>+0.6</td>
</tr>
<tr>
<td>Cooks</td>
<td>22 Aug 01</td>
<td>2.8</td>
<td>3.2</td>
<td>-0.4</td>
</tr>
<tr>
<td>Bwest</td>
<td>28 Jul 01</td>
<td>2.5</td>
<td>1.8</td>
<td>+0.7</td>
</tr>
<tr>
<td>BillSea</td>
<td>13 Aug 01</td>
<td>1.5</td>
<td>1.2</td>
<td>+0.3</td>
</tr>
</tbody>
</table>
The image-derived value is calculated from the total attenuation coefficient derived from the retrieved composition, and it does not include the spectral transfer function for the photopic human eye. If the differences between the image-derived and field-measured Secchi depths in Table 5 were due primarily to errors in retrieved composition, it would be expected that there would be a correlation of the Secchi depth differences in Table 5 with either the compositions or the compositional differences in one or more of Tables 2, 3, and 4. None of the compositional parameters in Tables 2, 3, and 4 have patterns that correlate with the differences in Table 5, however. This suggests that the differences in Table 5 could be due primarily to the differences in measurement approach.

**Comparison to QSC1**

QSC2 was designed to improve some of the limitations of an earlier version of the software (QSC1). QSC1 was based on the same radiative transfer foundation as the QSC2 software described here. A principal difference is that the earlier version required interactive user development of signatures based on “ground truth” information for the depth calculations. The number of required signatures depended on the variety of water quality conditions and bottom types in the image. The depth calculation process was described by Huguenin et al. (1997b). QSC1 retrieved water composition and water clarity using a separate formula, described below.

With QSC1, water quality information could be retrieved only for deep water (depths greater than 1.5 Secchi depth). The user needed to have some knowledge of the water quality characteristics of the visibly darkest water, $W(0,n)$, in the image. The user interactively selected a “water quality category” for that water. The choices included “Ocean,” “Coastal,” and five inland trophic status classes (Ultra-Oligotrophic, Oligotrophic, Mesotrophic, Eutrophic, or Hypereutrophic). Each of these categories had a standard model composition ($C_\text{eco}$, $C_\text{eco}$, and $C_\text{J}$) and a corresponding computed volume reflectance spectrum, $R_{\text{vol}}(0,n)$, $R_{\text{vol}}(n)$ for the water detection, $W(n)$, was then computed using the expression

$$R_{\text{vol}}(n) = \frac{\langle W(n)/W(0,n) \rangle \cdot R_{\text{vol}}(0,n)}{\langle R_{\text{vol}}(0,n) \rangle} \quad (15)$$

The composition for the water detection was then determined from $R_{\text{vol}}(n)$ using a three-dimensional pre-computed LUT approach, similar to the four-dimensional LUT used for QSC2. From the derived composition, the various water clarity parameters ($VSSR(n)$, $HSSR(n)$, and turbidity at three wavelengths, as well as depth confidence and turbidity confidence values) were computed and reported, as for QSC2.

A primary limitation of the water quality retrieval process in QSC1 is that the water quality characteristics of $W(0,n)$ are not always known. A second limitation is that errors due to bottom contribution for shallow water can significantly degrade the accuracy of the retrieved depth and water quality parameters. The water quality results from the original version were reasonably accurate, however, when the user had a reasonable knowledge of the trophic status of the darker waters, and bottom reflectance did not contribute appreciably to the upwelling radiance. By running the process in conjunction with the depth calculation model, the user could flag as potentially in error pixels having reported depths less than 1.5 $S$ or Turbidity Confidence values below a threshold value (0.8).

A comprehensive evaluation of depth accuracy of the earlier QSC1 software was carried out by the Naval Oceanographic Office (Remote Sensing Division, Integration and Technology Department, located at Stennis Space Center, Mississippi) at the request of the Advanced MASINT Branch of the National Air Intelligence Center/IXDA (Wright Patterson Air Force Base, Ohio). Details of this independent assessment and findings are available (on a need-to-know basis) from the Naval Oceanographic Office. The results are briefly summarized here.

The Navy test used Landsat Thematic Mapper imagery of study sites in California, Florida, North Carolina, and the Bahamas. Hydrographic surveys were conducted at each study site to provide sea truth for comparison to the bathymetric maps generated by the software. The analysis was complicated by the fact that precise depths were not provided as output from QSC1. Instead, the software binned depths into 15 discrete depth classes, having depth ranges that progressively increased with depth from ±2.0 meters at a 0.3-meter depth to ±3.2 meters at a 21.8-meter depth. An additional depth class included all reported depths greater than 25 meters. The hydrographic data were compared to the software output for the pixels collocated with the coordinates of the sea truth measurements. If the known depth fell within the reported depth class range at that location, the difference was recorded as zero. If the known depth fell outside of the classification range, the accuracy was determined by subtracting from the known depth either from the upper or lower limit of the range, depending on which calculation yielded the smaller result in an absolute sense. This resulted in an underestimate of errors.

The differences between the reported depths and sea truth were compiled to generate a mean and standard deviation. Means and standard deviations of errors for the four study areas were comparable. One of the study areas (6101 measurements) had a mean difference of −0.78 meters and a standard deviation of 1.9 meters. A second study area (1761 measurements) also had a mean difference of −0.78 meters and a standard deviation of 1.1 meters. A third area (1364 measurements) had a mean difference of +0.82 meters and a standard deviation of 0.99 meters. The fourth study area (1645 measurements) had a mean difference of +0.99 meters and a standard deviation of 2.1 meters. Factors that contributed to the differences were reported by the Navy to be poor satellite data quality, turbid water, heterogeneous atmospheric conditions, and inadequate sampling. Although a much smaller sample set, the depth differences reported for the Plymouth Harbor image using the QSC2 software were generally smaller than the differences reported using the earlier QSC1 version of the software.

A separate assessment of water composition performance using the earlier QSC1 software was done by NASA-Hyperspectral IODEP project. A detailed description is provided by Karaska et al. (2004). This NASA-sponsored study attempted to see if the QSC1 software could be used with AVIRIS imagery to predict harmful algae blooms in the Neuse River estuary in North Carolina. Nearly all of the water in the estuary was optically deep, and trophic status could be estimated with reasonable certainty. Consequently, the application was well suited to the requirements for QSC1. It was found that the image-derived measurements of suspended chlorophyll correlated well with field measurements ($r = 0.84$). The AVIRIS measurements of suspended minerals, colored dissolved organic carbon, and turbidity, however, could not be quantitatively evaluated, because of limitations of the field data. The reader is referred to Karaska et al. (2004) for detailed descriptions of the compositional accuracy assessment and Algae Production Potential Index (APP) derived from the compositional output planes.

**Discussion**

Comparisons of the two versions of the software reveals that QSC2 successfully addresses some of the principal limitations of the earlier version. The newer version eliminates the need for interactive signature derivation and the requirement for prior knowledge of water depths or water quality characteristics, without sacrificing accuracy. This is important for analyzing waters about which such knowledge is unavailable,
Plate 3. Image-derived concentrations of suspended chlorophyll (left), suspended sediments (center), and colored dissolved organic matter (right) for the Plymouth Harbor image shown in Plate 1.

Plate 4. Image-derived Vertical Subsurface Sighting Range at 445 to 516 nm (Band 1 bandpass) for the Plymouth Harbor image (left). The histograms for VSSR(n) for Bands 1 through 4 are shown for comparison (right).
Plate 5. (a) Image-derived Horizontal Subsurface Sighting Range at 445 to 516 nm (Band 1 bandpass) for the Plymouth Harbor image (left). The histograms for $HSSR(n)$ for the Bands 1 through 4 band passes are shown for comparison (right). (b) Image-derived Turbidity at 445 to 516 nm (Band 1 band pass) for the Plymouth Harbor image (left). The histograms for Turbidity for the Bands 1 through 4 band passes are shown for comparison (right).
and it suppresses errors caused by less-than-optimal signatures and incorrect user inputs. Furthermore, the ability of QSC2 to simultaneously retrieve water composition and depth, and to adaptively compensate for errors in the LUT values (through use of \( \text{SUN}_{\text{LUT}} \)) enables more uniform accuracies to be achieved over a broader range of surface reflectance (glint), water column, bottom, and depth characteristics.

This was confirmed by a demonstration of performance of the QSC2 software using a four-band Ikonos image of Plymouth, Massachusetts. Accuracies of the image-derived compositions, water clarity, and depths were assessed using field and laboratory measurements for eight representative lakes in the scene. The means of the differences of the field-measured and image-derived suspended chlorophyll and colored dissolved organic carbon concentrations for the eight lakes were 1.82 \( \mu \text{g/l} \) and 4.34 mgC/l, respectively. The image-derived concentrations of suspended sediments were all below the threshold of detection for the field samples (5 mg/l), in agreement with the field measurements. The mean of the differences between field-measured and image-derived Secchi depths (water clarity) and actual depths were 0.76 m and 0.57 m, respectively. In general, the agreement was good and uniform across the range of lakes sampled. The origins of the differences are uncertain, but are likely due primarily to the fundamental differences between the field and remote sensing measurement approaches.

A prime benefit of the output from the QSC2 software is the wide-area synoptic view of the various parameters that the software provides. This information provides spatially complete and simultaneous coverage of all water bodies in the image, in contrast to the typically non-simultaneous spot coverage provided by traditional field sampling. The output layers are two-dimensional maps of depth, water composition, and water clarity for a single point in time. This allows the spatial distribution of the various parameters to be analyzed and correlated with each other and with shoreline and inland features/phenomena without the complicating influence of temporal variability. Temporal variations of these relationships can be assessed in a controlled manner through repeat coverage over multiple dates. The patterns and changes in parameters over time (with multitemporal coverage) in the output layers provide critical insights and information about the sources and causes of phenomena responsible for the status of the water body. Agencies responsible for water quality monitoring under the Clean Water Act provisions would benefit greatly from this type of information.

Acknowledgments

The authors greatly acknowledge the contributions of Brad Thomson, Melanie Harlow, and Dr. John Mustard of the NASA Affiliated Research Center at Brown University. The Ikonos imagery used in this study was provided to GeoSyntec as part of a different project and its purchase was funded by the NASA ARC Program. The authors would also like to thank the following parties for their integral role in this research: the Massachusetts Watershed Initiative, EPA Alpha Analytical Labs, Region 1 Laboratories, U.S. Environmental Rental Corporation, Aquatic Control Technologies, and GeoLabs Inc, for support and assistance with laboratory analysis. Portions of this work were supported by internal research and development funds by both Applied Analysis Incorporated of Billerica, Massachusetts and GeoSyn- tec Consultants.

References


