Retrieval of the diffuse attenuation coefficient from GOCI images using the 2SeaColor model: A case study in the Yangtze Estuary

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Abstract: The 2SeaColor model (Salama and Verhoef, 2015) was proposed to analytically retrieve the diffuse attenuation coefficient (K_d) from remote sensing reflectance (R_{rs}), but its parameterization was based on approximations and subjected to large uncertainties. In this study, we present an improvement on the parametrization equations in the inverse scheme of the 2Seacolor model. The improved model is then validated with three *in-situ* datasets and compared with the Zhang model (Zhang and Fell, 2007) and the Lee model (Lee et al., 2005a). Validation with radiometric data shows that the 2SeaColor model provides the best estimates of K_d for the full range of observations, with the largest determination coefficient ($R^2 = 0.935$) and the smallest root mean squared error (RMSE = 0.078 m^{-1}). For clear waters, where $K_d(490) < 0.2$, the Zhang model provides the most accurate K_d estimations, but results from the Lee model and the 2SeaColor are rather comparable. For turbid waters, where $K_d(490) > 0.2 \text{ m}^{-1}$, the 2SeaColor model is found to be

more accurate, with an RMSE of 0.186m^{-1} , compared to RMSEs of 0.279 m^{-1} and 0.388 m^{-1} for the Zhang model and the Lee model, respectively.

The 2SeaColor model is finally applied to the GOCI (Geostationary Ocean Color Imager) level 2 product (L2P) to produce K_d maps over the Yangtze estuary, resulting in a reasonable distribution and expected range of K_d , as for example $K_d(490)$ was varying from 0.04 to 9.82 m^{-1} for the image acquired at 02:16 UTC, on March 8th 2013.

The analytical 2SeaColor model is able to provide consistently stable and fairly accurate K_d estimates in both clear and turbid waters without the need of tuning empirical coefficients from field measurements, and thus has great potential for estimating K_d over optically complex waters.

Key words: diffuse attenuation coefficient, 2SeaColor, GOCI, Yangtze Estuary

1. Introduction

The diffuse attenuation coefficient (K_d , in m^{-1}) is an important optical property of water bodies that describes the penetration of incident solar radiation in the water column. K_d is classified as a quasi-inherent optical property (QIOP), since it depends on both the optically active water constituents and the distribution of the ambient light field (Kirk, 1984, 1991; Mobley, 1994; Smith and Baker, 1978).

Based on the fact that 90% of the diffusely reflected light from a water body comes from a surface layer of water within a depth of $1/K_d\text{ m}$, the diffuse attenuation coefficient shows potential effects on the functioning of ecological processes and biogeochemical cycles in oceanic and coastal ecosystems. Previous researches have shown that K_d can be an effective indicator for turbidity in water (Kirk, 1994) and sediment transportation and resuspension (Majozi et al., 2014; Zhang et al.,

2006). Meanwhile, K_d is a key parameter in studies such as heat transfer in the upper water layer (Stramska and Zuzewicz, 2013; Wu et al., 2007), phytoplankton photosynthesis and photobleaching (Loiselle et al., 2009; McClain et al., 1996), and the estimation of primary production in natural waters (Bergamino et al., 2010; Lee et al., 2011).

Algorithms for the remote retrieval of K_d have been developed for clear waters (Austin and Petzold, 1981; Mueller, 2000), but they always generate huge errors in turbid waters due to the complexity in optical properties and limitations in the algorithms (IOCCG, 2000, 2006; Salama et al., 2011; Zibordi et al., 2009). To retrieve K_d in optically complex waters, several methods were adopted. The empirical models were developed by statistical fitting based on *in-situ* measurements (Werdell and Bailey, 2005; Zhang and Fell, 2007). The semi-analytic models usually calculated the K_d from remotely retrieved inherent optical properties (IOPs) of water constituents (Doron et al., 2007; Lee et al., 2005a; Lee et al., 2005b; Morel and Loisel, 1998; Wang et al., 2009a). Additionally, Salama and Verhoef (2015) developed the analytical 2SeaColor model to estimate K_d at different spectral bands and depths, based on the solution of the radiative transfer equation using the two-stream approximation. The two-stream approximation was previously adopted in the retrieval of suspended matter (Ambarwulan et al., 2012; Shen et al., 2010). However, the assumption in the original 2SeaColor model that only water molecules contribute to the total absorption in the near-infrared (NIR) bands may not work for highly turbid waters, which leads to large uncertainties for observations from turbid waters. Therefore, improvement on the 2SeaColor model is strongly desired for K_d estimation over turbid waters. The objective of this study is to improve the 2SeaColor model and validate the respective performance of the 2SeaColor model and other empirical and semi-analytical models. We first improve the parameterizations in the inversion scheme of the 2SeaColor model. Then the 2SeaColor model is validated with three *in-situ* datasets and compared

66 with empirical and semi-analytic models. At last, we produce K_d maps over the Yangtze Estuary by
67 operating the 2SeaColor model on the level 2 product (L2P) of the Geostationary Ocean Color
68 Imager (GOCI).

69 **2 Material and methods**

70 **2.1 Data sets**

71 Three *in-situ* datasets are employed in this study for model validation and inter-comparison,
72 which are collected from a variety of waters covering from open ocean to coastal regions. They are
73 the NOMAD (NASA Bio-Optical Marine Algorithm Data set) (Werdell and Bailey, 2005), the
74 COASTLOOC (Coastal Surveillance through Observation of Ocean Color) (Babin et al., 2003) and
75 *in-situ* measurements in Yangtze estuarine and coastal water, hereafter denoted as the Yangtze
76 dataset. Fig.1 presents the locations of the *in-situ* observations of these three datasets. Solar zenith
77 angle (SZA, in degree) of each observation is calculated according to location (latitude and
78 longitude and time zone), date and time (C++ code is available
79 at <http://www.psa.es/sdg/sunpos.htm>). The percentage distribution of SZA for each dataset is
80 presented in Fig.2.

Fig. 1. Location of the field data sets. (a) The NOMAD, (b) the COASTLOOC and (c) the Yangtze data set (solid circles are matchups sites within 1h overpass of GOCI).

84
85 **Fig. 2.** Percentage distribution of solar zenith angle (SZA) in the three in-situ data sets.

86 *2.1.1 NOMAD dataset*

87 The NOMAD dataset (Werdell and Bailey, 2005) contains 4459 observations of bio-optical
88 parameters collected worldwide from open ocean to coastal waters. Observations were selected
89 where the upwelling water radiance (L_w) and the spectral downwelling irradiance (E_s) in the bands at
90 411, 443, 489, 510, 555, and 665 nm are all valid, as well as the diffuse attenuation coefficient at
91 443 and 489 nm. As a result, 1518 concomitant observations were selected (sampled sites are shown
92 in Fig. 1a). The diffuse attenuation coefficient at 489nm, $K_d(489)$, of the selected observations
93 ranges from 0.0085 m^{-1} to 0.9113 m^{-1} with an average value of 0.0852 m^{-1} and a standard deviation
94 of 0.105 m^{-1} . Remote sensing reflectance (R_{rs}) is calculated as the ratio of upwelling water radiance
95 L_w to the downwelling irradiance E_s , and $K_d(489)$ is considered equivalent to $K_d(490)$ for model
96 validation and inter-comparison in this study.

98 2.1.2 COASTLOOC dataset

99 The COASTLOOC dataset (Babin et al., 2003) consists of 422 observations of bio-optical
100 parameters collected from European coastal waters. The irradiance reflectance just below the sea
101 surface $R(0^-)$ is available in the COASTLOOC data set instead of R_{rs} . Therefore, the $R(0^-)$ was
102 converted to R_{rs} using the formulation used in Zhang and Fell (2007): $R_{rs} = 0.133R(0^-)$. It is worthy
103 to mention that this formulation uses a constant value for the upwelling irradiance-to-radiance ratio
104 ($Q = 4$), which will definitely generate uncertainties to the calculated R_{rs} . However, the effect of the
105 Q value on the derived K_d is limited when the ratio of R_{rs} or the spectral optimization technique is
106 used, which will cancel out much of the dependencies. The COASTLOOC dataset was also filtered
107 and 217 concomitant observations were selected where R_{rs} and K_d in the bands at 411, 443, 489, 510,
108 555, 665 and 705 nm are all valid, as well as the solar zenith angle θ_s (sampled sites are shown in
109 Fig. 1b). The $K_d(490)$ of the selected observations ranges from 0.025 m^{-1} to 2.976 m^{-1} with an
110 average value of 0.490 m^{-1} and a standard deviation of 0.487 m^{-1} .

111 2.1.3 Yangtze dataset

112 The Yangtze dataset was collected during a cruise campaign in the Yangtze estuarine and coastal
113 water from 4th to 19th of March, 2013. This dataset consists of 29 measurements of R_{rs} and K_d
114 (sampled sites are shown in Fig. 1c). Radiometric measurements were recorded by the Hyperspectral
115 Surface Acquisition System (HyperSAS, Satlantic Inc., Canada), consisting of the sea-surface
116 radiance (L_t), sky radiance (L_i) and solar irradiance (E_s) from 350 to 900nm in 136 spectral
117 channels. Details about sensors mounting and observation geometries can be found in Shen et al.
118 (2014). R_{rs} was calculated by (Hooker et al., 2002; Mobley, 1999):

$$119 \quad R_{rs} = \frac{L_w}{E_s} = \frac{L_t - \rho L_i}{E_s}, \quad (1)$$

120 where ρ is the sea surface reflectance factor which is a function of solar zenith angle and surface
121 roughness. The Ruddick-Hojerslev model (RHM) (Ruddick et al., 2006) is adopted here to compute
122 the ρ (See Table 6 in Sokoletsky and Shen (2014)).

123 Vertical profiles of underwater downwelling planar irradiance, $E_d(\lambda, z)$, were recorded by the
124 Hyperspectral Ocean Color Radiometer (HyperOCR, Satlantic Inc., Canada), which provides 136
125 channels of factory calibrated optical data from 350 to 800nm. K_d is calculated as the absolute slope
126 of a linear regression fitting between $\ln[E_d(\lambda, z)]$ and depth z (Darecki and Stramski, 2004; Kirk,
127 1994). For the calculation of K_d in the surface layer, $E_d(\lambda)$ between 0.6 and 2m with a 0.1m interval
128 are used in the linear regression, and results with determination coefficients larger than 0.99 are
129 accepted. Field measured R_{rs} and K_d are presented in Fig. 3. The K_d spectrum is smoothed using the
130 adjacent-averaging method (explanation at [http://www.originlab.com/doc/Origin-Help/Smooth-](http://www.originlab.com/doc/Origin-Help/Smooth-Algorithm)
131 [Algorithm](http://www.originlab.com/doc/Origin-Help/Smooth-Algorithm)). $K_d(490)$ in the Yangtze data set ranges from 0.179 m⁻¹ to 3.462 m⁻¹ with an average
132 value of 1.229 m⁻¹ and a standard deviation of 0.968 m⁻¹.

133

134 **Fig. 3.** Field measured spectra of $R_{rs}(\lambda)$ and $K_d(\lambda)$ of the Yangtze dataset.

135 **2.2 GOCI images and atmospheric correction**

136 GOCI (2010 - present) is a geostationary-orbiting ocean color instrument with a spatial resolution
 137 of 500m. It acquires data in 8 spectral bands (6 visible and 2 NIR) and 8 images are available for the
 138 Yangtze Estuary during daytime from 00:15 UTC to 07:45 UTC (Ryu et al., 2012). The central
 139 wavelengths are 412, 443, 490, 555, 660, 680, 745 and 865nm. A maximum of three images are free
 140 for download before the year 2014 from the official website
 141 (http://hero911.dothost.co.kr/list_GOCI.php?dir=/GOCI/1.0), while all images are free to access
 142 since 2014. Six *in-situ* measurements were sampled within 1h of GOCI overpass and selected as
 143 matchups in this study. A match-up set is the pair of a 3-by-3 satellite pixel box and an *in-situ* site
 144 matching in location and sampling time. The average value of the 3-by-3 pixel box is used as the
 145 matched value of R_{rs} and K_d . The matched images were acquired on 03:04 UTC and 04:16 UTC of
 146 March 4th (the matchups sites are A1-1 and A1-2 in Fig. 1c), 02:16 UTC of March 5th (A2-7 in Fig.

147 1c), 02:16 UTC of March 8th (A6-3 and A6-4 in Fig.1c) and 04:16 UTC of March 9th (A7-2 in
148 Fig.1c).

149 In this study, we corrected GOCI image using the standard atmospheric correction algorithm
150 (Ahn et al., 2012) which is implemented in GDPS (GOCI Data Processing System) version 1.3. This
151 algorithm is theoretically based on the SeaWiFS method (Gordon and Wang, 1994) with
152 modifications for turbid waters where the black pixel assumption is invalid (Goyens et al., 2013; Hu
153 et al., 2000; Salama et al., 2004; Salama and Shen, 2010a; Wang and Shi, 2007; Wang et al., 2009b).
154 To improve the accuracy of retrieved water-leaving reflectance in turbid waters, GDPS version 1.3
155 adopts method of Hu et al. (2000) to select the nearest non-turbid pixels for deducing NIR water
156 leaving reflectance in turbid waters, and uses the NIR R_{rs} empirical relationship of Ruddick et al.
157 (2000) for constraining the AC. A brief algorithm description of GDPS version 1.3 can be found
158 at http://222.236.46.37/GDPS/ATBD_master_v9.pdf. The GOCI level 2 product (L2P) from GDPS
159 including remote sensing reflectance (R_{rs}), which is used in this study to produce maps of diffuse
160 attenuation coefficient.

161 **2.3 The 2SeaColor model**

162 The 2SeaColor model is based on the solution of the two-stream radiative transfer equations
163 including direct sunlight, as described by (Duntley, 1942, 1963). Both the analytical forward model
164 and the inversion scheme are provided in detail in Salama and Verhoef (2015). To analytically
165 derive K_d from R_{rs} , the first step is to derive the IOPs (total absorption a and backscattering
166 coefficients b_b) from R_{rs} in the inversion scheme using spectral optimization, after which K_d is
167 calculated from the derived IOPs using the analytical forward model.

168 The reflectance result predicted by the 2SeaColor model is r_{sd}^{∞} , the directional-hemispherical
 169 reflectance of the semi-infinite medium, which is linked to IOPs by (Salama and Verhoef, 2015):

$$170 \quad r_{sd}^{\infty} = \frac{\sqrt{1+2x}-1}{\sqrt{1+2x}+2\mu_w}, \quad (2)$$

171 where x is the ratio of backscattering to absorption coefficients ($x = b_b/a$), and μ_w is the cosine of
 172 the solar zenith angle beneath the water surface.

173 The reflectance factor r_{sd}^{∞} can be approximated by Qr_{rs} under sunny conditions, where $Q \sim 3.25$.
 174 r_{rs} is remote sensing reflectance beneath the surface (Morel and Gentili, 1993), which can be
 175 converted from above-surface remote sensing reflectance (R_{rs}) by (Lee et al., 2002):

$$176 \quad r_{rs} = \frac{R_{rs}}{0.5+1.7R_{rs}}, \quad (3)$$

177 In the original 2SeaColor model, water molecules are assumed to be the only contributor to
 178 absorption in the NIR band. The total backscattering coefficient (b_b) at the NIR band is estimated
 179 from the ratio x and the water absorption coefficient, then b_b (NIR) can be extrapolated to shorter
 180 wavelengths using the Eq. (4). At last, the total absorption coefficient is derived from $b_b(\lambda)$ and the
 181 ratio $x(\lambda)$ from Eq. (2) and Eq. (3).

$$182 \quad b_{bp}(\lambda) = b_{bp}(\lambda_0) \left(\frac{\lambda_0}{\lambda} \right)^Y, \quad (4)$$

183 where λ_0 is the reference wavelength and Y is the power law exponent for the particle backscattering
 184 coefficient.

185 In this paper, we propose an improvement on the parameterizations in the inversion scheme of
 186 the2SeaColor model. Absorption and backscattering coefficients of water molecules (a_w and b_{bw})
 187 are taken from a previous study (Mobley, 1994; Morel, 1974; Smith and Baker, 1981). As
 188 implemented in Salama and Shen (2010b), absorption and backscattering coefficients of water

189 constituents are parameterized by (Bricaud et al., 1981; Lee et al., 1998; Lee et al., 1999;
190 Sathyendranath et al., 2001):

$$191 \quad a_{\varphi}(\lambda) = (a_0(\lambda) + a_1(\lambda) \ln[a_{\varphi}(440)]) a_{\varphi}(440), \quad (5)$$

$$192 \quad a_{dg}(\lambda) = a_{dg}(\lambda_0) e^{-s(\lambda-\lambda_0)}, \quad (6)$$

193 where the subscript φ stands for chlorophyll and a_0 and a_1 are given in Lee et al. (1998), the
194 subscript dg stands for the combination of CDOM and non-algae particles and S is the spectral slope
195 of the combined absorption coefficient.

196 Initial values of $a_{\varphi}(440)$, $a_{dg}(\lambda_0)$, $b_{bp}(\lambda_0)$ and Y were adopted from Lee et al. (1999) based on
197 band-ratios of R_{rs} . S is ranged between 0.013 and 0.017 nm^{-1} according to field observations (Lee et
198 al., 2002), and an average value of 0.015 nm^{-1} is used in Lee's QAA model (Lee et al., 2002) and its
199 updated version (QAA_v4, Lee et al. (2007)). This average value of S is also adopted in this study.
200 In this way, no tuning of empirical coefficients and no field data except the measured R_{rs} are
201 required in the inversion scheme. With these parameterizations of absorption and backscattering
202 coefficients, R_{rs} can be reconstructed according to Eq. (2) and Eq. (3). For each set of values for the
203 four unknowns, a spectral optimization program using nonlinear curve fitting was applied that
204 computes the sum of squared differences between the model-simulated R_{rs} curves and the field
205 measured R_{rs} curves and iterates until the minimum is reached. At that point, values of $a_{\varphi}(440)$,
206 $a_{dg}(\lambda_0)$, $b_{bp}(\lambda_0)$ and Y are considered to be retrieved. K_d is then calculated from the derived IOPs
207 according to the analytical forward model described in Appendix B in Salama and Verhoef (2015).

208 **2.4 The Zhang model and the Lee model**

209 To evaluate the performance of the 2SeaColor model, we compare the 2SeaColor model with
210 previous reported empirical and semi-analytical models. The candidate empirical model is the Zhang
211 model (ratio-based) (Zhang and Fell, 2007), and the semi-analytical model is the Lee model (IOPs-
212 based) (Lee et al., 2005a; Lee et al., 2005b).

213 (i) The Zhang model:

214 If $\frac{R_{rs}(490)}{R_{rs}(555)} \geq 0.85$ then $K_d(490) = 10^{(-0.843-1.459X-0.101X^2-0.811X^3)} + 0.016,$

215 where $X = \log_{10}\left(\frac{R_{rs}(490)}{R_{rs}(555)}\right);$ (7)

216 If $\frac{R_{rs}(490)}{R_{rs}(555)} < 0.85$ then $K_d(490) = 10^{(0.094-1.302X+0.247X^2-0.021X^3)} + 0.016,$

217 where $X = \log_{10}\left(\frac{R_{rs}(490)}{R_{rs}(665)}\right);$ (8)

218 (ii) The Lee model: Total absorption and backscattering coefficient, $a(\lambda)$ and $b_b(\lambda)$, are first derived
219 from remote sensing reflectance by the 2SeaColor model using the spectral optimization. $K_d(490)$ is
220 then calculated according to the following equation (Lee et al., 2005a):

221 $K_d(490) = (1 + 0.005\theta_s)a(490) + 4.18(1 - 0.52e^{-10.8a(490)})b_b(490)$ (9)

222 where θ_s is the sun zenith angle.

223 **2.5 Data analysis**

224 Five statistical parameters are used to quantitatively evaluate the goodness-of-fit between derived
225 and known values. They are the slope and intercept of the regression line, the determination

coefficient R^2 , the mean of absolute relative difference (rMAD) and the root mean square error (RMSE). The rMAD and RMSE are defined as follows:

$$\text{rMAD} = \sum |1 - \text{derived}/\text{known}| / N \times 100\%, \quad (10)$$

$$\text{RMSE} = \sqrt{\sum (\text{derived} - \text{known})^2 / N}, \quad (11)$$

where N is the number of observations. Additional parameters such as percentage of observations within 25% and 100% relative error (F25 and F100, respectively) are also provided.

3 Results

3.1 Improvement on the parameterizations

Considering R_{rs} in the NIR bands (>750 nm) are absent in both the NOMAD and the COASTLOOC datasets, comparison between the original 2SeaColor and the improved version proposed in this study is made on the Yangtze dataset and the IOCCG (International Ocean Colour Coordinating Group) synthetic dataset. The IOCCG dataset is available at http://www.ioccg.org/groups/OCAG_data.html, and the synthetic data for the sun at 30° from zenith is used in this study. The comparison is presented in Fig. 4. As shown in Fig. 4a, the original 2SeaColor seems to overestimate K_d systematically for observations with high K_d . It is more obvious in Fig. 4b that the improved version provides more accurate K_d estimations for the Yangtze dataset compared to the original one.

Fig. 4 Comparison between the original 2SeaColor model and the 2SeaColor model with improved parameterizations for (a) IOCCG dataset and (b) Yangtze dataset.

3.2 Validation and inter-comparison for K_d retrieval models

Three in-situ datasets described in [Section 2.1](#) are used to validate the 2SeaColor model. The performance of the 2SeaColor model is compared with the empirical Zhang model and the semi-analytical Lee model with IOPs derived from the 2SeaColor model. [Fig. 5](#) shows the known versus derived $K_d(490)$ for all K_d retrieval models applying on three in-situ datasets. In order to get a better understanding of these models and their limitations, we divide the three datasets into two subsets for observations from clear and turbid water, respectively. The threshold used in the Zhang model is adopted here, which is corresponding to $K_d(490) = 0.2 \text{ m}^{-1}$. This threshold is also considered as an upper limit for simple empirical algorithms ([Lee et al., 2013](#); [Lee et al., 2005a](#)).

255

256 **Fig. 5.** Known versus derived $K_d(490)$ for (a) Zhang model, (b) Lee model and (c) 2SeaColor model, applied to all three
 257 data sets. The insets with smaller markers show the results for low $K_d(490)$ observations where known $K_d(490) \leq 0.2 m^{-1}$.

258 The overall performance of the 2SeaColor model is better than that of the other two models with
 259 data points well distributed around the 1:1 line (see Fig. 5c). The Lee model seems to overestimate
 260 K_d in turbid waters as shown in Fig. 5b, especially for the Yangtze dataset, while the Zhang model
 261 seems to systematically underestimate K_d in turbid waters as shown in Fig. 5a. From the insets in
 262 Fig. 5, we can find that both the Lee model and the 2SeaColor model generate larger errors for some
 263 observations from clear water where $K_d(490) \leq 0.2 m^{-1}$. Statistical results for the $K_d(490)$ estimation
 264 from all three models are listed in Table 1.

265 As presented in Table 1, we can observe that derived $K_d(490)$ from the 2SeaColor for the full
 266 range of observations is most accurate with the highest R^2 ($= 0.935$) and the smallest RMSE ($=$
 267 $0.078 m^{-1}$), compared to the Zhang model ($R^2 = 0.898$ and $RMSE = 0.113 m^{-1}$) and the Lee model (R^2
 268 $= 0.885$ and $RMSE = 0.157 m^{-1}$). For observations from turbid waters where $K_d(490) > 0.2 m^{-1}$, the
 269 2SeaColor model provides most accurate K_d estimations, where the RMSE of the Zhang model and
 270 the Lee model are 50 % and 109% greater than that of 2SeaColor. The highest R^2 ($= 0.891$) and the

smallest rMAD (= 21.56%) are also found for retrievals from the 2SeaColor model for turbid water observations. Predictions from the 2SeaColor are stable with 64.18% of the estimations confined within a 25% relative error margin and 99.29% of the estimations confined within a 100% relative error margin. For clear waters where $K_d(490) \leq 0.2\text{m}^{-1}$, the Zhang model provides best estimates with almost unity slope, the smallest rMAD (= 21.26%) and RMSE (= 0.017 m^{-1}). However, the performance of the 2SeaColor in this case are rather comparable in terms of both RMSE (= 0.020 m^{-1}) and rMAD (= 22.58%).

Compared to the 2SeaColor model, the slopes from the linear regression of derived and known $K_d(490)$ of the Zhang model and the Lee model are far off unity, especially in turbid waters where the slope is more than 30% off unity for the Zhang model and almost 50% off unity for the Lee model. The difference in the slope indicates that predictions from the Zhang model will be underestimated with increasing K_d , while predictions from the Lee model will be overestimated with increasing K_d .

Table 1 Statistical results of three K_d retrieval models with respect to observations divided into two subsets with a threshold of $K_d(490) = 0.2\text{m}^{-1}$.

	All (N=1764)			$K_d(490) \leq 0.2\text{m}^{-1}$ (N=1481)			$K_d(490) > 0.2\text{m}^{-1}$ (N=283)		
	Zhang	Lee	2SeaColor	Zhang	Lee	2SeaColor	Zhang	Lee	2SeaColor
Slope	0.769	1.325	0.929	1.099	1.162	1.125	0.686	1.468	0.908
Intercept	0.014	-0.03	0.012	-0.013	-0.002	-0.001	0.093	-0.203	0.023
R^2	0.898	0.885	0.935	0.879	0.845	0.846	0.824	0.835	0.891
RMSE	0.113	0.157	0.078	0.017	0.021	0.020	0.279	0.388	0.186
rMAD	21.78	23.32	22.43	21.26	22.99	22.58	24.52	25.03	21.56
F25	63.27	67.74	67.46	64.55	67.99	68.13	56.38	66.43	64.18
F100	99.72	98.47	99.09	99.66	98.71	99.05	100.00	97.17	99.29

3.3 Estimating K_d from GOCI images

3.3.1 Atmospheric correction for GOCI image

To demonstrate the performance of the GOCI standard atmospheric correction algorithm, we compared the field measured R_{rs} and the R_{rs} product of GOCI at six matchups sites (Fig. 6). The

289 GOCI standard atmospheric correction algorithm implemented in GDPS 1.3 generates an acceptable
 290 error with $RMSE = 0.005 \text{ sr}^{-1}$ and $rMAD = 27.30\%$, which is in accordance with the expected error
 291 (Salama and Stein, 2009; Wang et al., 2009b). Note that only seven bands were adopted in the
 292 comparison because $R_{rs}(865)$ is not available in the Yangtze dataset.

293
 294 **Fig. 6.** Comparisons between field measured R_{rs} and GOCI R_{rs} product for six matchups at each GOCI bands except
 295 band 865nm.

296 It is worthy to mention that the GOCI standard atmospheric correction masks out highly turbid
 297 pixels in some of the matched images, even in some of the clear water pixels in this study, which
 298 was also reported in previously published results (Hu et al., 2012; Shen et al., 2014). However,
 299 developing a more accurate atmospheric correction or recovering the masked pixels (Nordkvist et al.,
 300 2009) is out of the scope of this study. The GOCI standard atmospheric correction is considered
 301 appropriate for us to focus our study on the retrieval and validation of diffuse attenuation coefficient.

302 3.3.2 Producing K_d maps using the 2SeaColor model

303 To better present the distribution of K_d over the Yangtze estuary, we selected an image with
304 minimum number of masked pixels from all matched images, which was captured at 02:16 UTC, on
305 8th March 2013. The 2SeaColor model was applied to the L2P product of this image to produce K_d
306 maps over the Yangtze estuary at wavelengths of 440, 490, 550 and 640nm, respectively. The
307 produced K_d maps are shown in Fig. 7.

308

309 **Fig. 4.** K_d derived from atmospherically corrected GOCI image using the 2SeaColor model. Four wavelengths are shown:
310 (a) 440nm, (b) 490nm, (c) 550nm and (d) 640nm.

311 The spatial distribution of the diffuse attenuation coefficient at the four chosen wavelengths
312 shows the same pattern. A wide range of K_d is observed as high K_d values are present in nearshore

313 waters, especially in Hangzhou bay and the North Branch of the Yangtze Estuary (see [Fig. 1c](#)),
314 while K_d in offshore waters is about 1~2 orders of magnitude lower. For instance, in [Fig. 7b](#), $K_d(490)$
315 reaches approximately 10 m^{-1} in some pixels in Hangzhou Bay and the North Branch but keeps
316 steadily low around 0.1 m^{-1} in offshore waters. The K_d maps confirm that both Hangzhou bay and
317 the Yangtze Estuary (especially the North Branch) are extremely turbid waters, which is highly
318 consistent with the known distribution of suspended matter in this area ([Shen and Verhoef, 2010](#);
319 [Shen et al., 2010](#); [Shen et al., 2013](#); [Shen et al., 2014](#)).

320 From [Fig. 7](#) we can observe that K_d decreases from 440nm to 640nm in nearshore waters, but K_d
321 at 640nm in offshore waters is higher than at other wavelengths. The difference between the K_d
322 spectra in clear and turbid waters can also be found in other published studies ([Lee et al., 2013](#)) as
323 well as in field measurements in the Yangtze dataset (see [Fig. 3b](#)). The nature of this behavior is the
324 difference in the constituents between clear and turbid waters. For turbid water in the Yangtze
325 estuary, where suspended particulate matter (SPM) and CDOM dominate the inherent optical
326 properties (IOPs), namely a higher absorption coefficient as well as a higher backscattering
327 coefficient at short wavelengths, which leads to a higher K_d value in this range. For clear water
328 where chlorophyll and water molecules dominate the IOPs, the behavior of the K_d spectrum is
329 mainly determined by the tremendous increase of the absorption coefficient of water molecules
330 beyond 600nm.

331 4 Discussion

332 4.1 The improved 2SeaColor model

333 The improved 2SeaColor model with adopted parameterization provides better estimation of
334 retrieved $K_d(490)$, which proves that the assumption in the original parameterization of the
335 2SeaColor model is not valid for turbid waters. This is because the absorption coefficient in turbid
336 waters is far more complex than the backscattering coefficient, and the 2SeaColor model will
337 generate uncertainty if no *prior* knowledge on the absorption coefficient is available. Water
338 molecules are not the only absorbing material in the NIR region in turbid waters, as laboratory
339 experiments by [Röttgers and Gehnke \(2011\)](#) showed that natural water samples with high amounts
340 of detrital material still absorb strongly in the NIR region after removing the contribution from the
341 water molecules. Compared to the original 2SeaColor model that requires NIR spectral data, the
342 improved parameterizations will enable the 2SeaColor model to be applied to dataset without NIR
343 spectral data such as the NOMAD and COASTLOOC datasets.

344 On the other hand, total absorption and backscattering coefficients (a and b_b) derived from the
345 improved 2SeaColor model are within acceptable uncertainties for both clear and turbid waters. [Fig.](#)
346 [8](#) shows the validation of $a(490)$ and $b_b(490)$ derived from the improved 2SeaColor model using
347 matched observations from the NOMAD and COASTLOOC datasets. For the NOMAD dataset, the
348 accuracy of derived $a(490)$ from the 2SeaColor model (Fig. 8a) is promising with R^2 of 0.708 and
349 RMSE of 0.708 m^{-1} . The accuracy of derived $b_b(490)$ (Fig. 8c) is also robust with R^2 of 0.558 and
350 RMSE of 0.001 m^{-1} . As for the COASTLOOC dataset, the comparison between derived $a(490)$ from
351 the 2SeaColor model and known $a(490)$ (Fig. 8b) also shows good accordance with R^2 of 0.794 and
352 RMSE of 0.201 m^{-1} . Note that no matched $b_b(490)$ is available in the COASTLOOC dataset.

Fig. 5 Validation of 2SeaColor-derived total absorption and backscattering coefficient at 490nm, $a(490)$ and $b_b(490)$, using matched observations in the NOMAD and COASTLOOC datasets. Note the difference in scales for $a(490)$ in both cases.

4.2 Assessments of K_d retrieval models

Empirical models based on simple blue/green R_{rs} ratios are always deemed unsuitable for turbid coastal waters and considerably underestimate K_d by a factor of 2 ~ 3 or more in turbid waters (Chen et al., 2014; Sun et al., 2014; Wang et al., 2009a). This is mainly because remote sensing reflectance in the blue and green bands is mainly affected by detrital material and gelbstoff in turbid waters. These two constituents absorb strongly in the blue region, which makes the water-leaving signal continually low in the blue region. Therefore, variations in the mixture of detrital material and gelbstoff may not affect the blue/green ratios of R_{rs} , but have huge effects on the diffuse attenuation coefficient. Both the Zhang model and the Lee model have often been applied in model inter-comparisons and were validated against various field measurements, showing that they were suitable for K_d retrieval in both clear and turbid waters (Jamet et al., 2012; Lee et al., 2005b; Zhang and Fell, 2007). Results in this study show that derived K_d from the 2SeaColor model is comparable with

369 these two models in clear waters, while the 2SeaColor has better performance over highly turbid
370 waters.

371 The good performance for the Zhang model and the Lee model in clear water can be attributed to
372 the fact that the empirical coefficients in these models have already been fine-tuned to clear waters
373 during model development. For clear waters, where in most cases chlorophyll and water molecules
374 dominate the optical properties, the variability of optical properties is rather limited compared to
375 those of turbid waters. Therefore, the fine-tuned empirical or semi-analytical model should always
376 work well for clear waters. However, when it comes to turbid waters, the empirical models generate
377 large uncertainty since the fine-tuned coefficients are not suitable for optical complex waters and a
378 fine-tuning of the empirical coefficients would be required (Mitchell et al., 2014; Qiu et al., 2013).
379 This is one of the main reasons that the empirical Zhang model systematically underestimates K_d
380 and the semi-analytical Lee model overestimates K_d in turbid waters.

381 Additionally, K_d is considered as sun-angle dependent and the ratio-based models are most likely
382 to represent only the diffuse attenuation at a fixed angle (Lee et al., 2013). As for the three datasets,
383 the percentage distribution (Fig. 2) shows a large variation in sun zenith angle, the mis-match in sun
384 zenith angle would result in large errors for the Zhang model. As presented in Fig. 2, most
385 observations were measured at sun zenith angles larger than 40° , especially for the COASTLOOC
386 and the Yangtze datasets (the percentage are 85.71% and 75.86, respectively). A large sun zenith
387 angle usually results in a higher K_d due primarily to the increased photon path length in water (Lee
388 et al., 2013). The mis-match can be corrected for the IOPs-based Lee model and the 2SeaColor
389 model where the sun zenith angle is used as an input parameter. However, for the Zhang model, the
390 mis-match in sun zenith angle could contribute to the large uncertainty of derived K_d in turbid waters.

391 As for the Lee model, the contribution rate of b_b to K_d is empirically modeled , which means
392 estimations from the Lee model in turbid waters will also involve larger uncertainties without
393 adapting the empirical coefficients. Another reason for the large uncertainty in turbid waters for the
394 Lee model is that the scattering coefficient in turbid waters tends to become more significant in the
395 forward direction, while the Lee model totally ignores this forward scattering. The forward
396 scattering may have little effect on the reflectance, but it has a large effect on K_d .

397 In contrast, the success of the 2SeaColor for clear and turbid waters should be attributed to both
398 the analytical forward model and its inversion scheme. The analytical forward model takes forward
399 scattering into account by applied the similarity transformation and estimates K_d based on radiative
400 transfer physics, while the inversion scheme, with improved parameterizations, can accurately
401 derive the absorption and backscattering coefficients using the spectral optimization technique. In
402 general, advantages of the 2SeaColor model are: (i) no empirical relationships are involved and a
403 fine-tuning of empirical coefficients is avoided; (ii) no *prior* knowledge on optical properties of the
404 regions of interest is required; (iii) only the spectrum of remote sensing reflectance is necessary; (iv)
405 it provides consistently accurate estimations for both clear and turbid waters. With these advantages,
406 we can state that 2SeaColor has little limitations due to regional variability in optical properties.
407 Thus, 2SeaColor forms an attractive optional solution for the retrieval of K_d from Earth Observation
408 data for both clear and turbid waters. Furthermore, to produce the best diffuse attenuation coefficient
409 for an image at a large spatial scale covering both clear and turbid waters, a blended algorithm
410 combining the Zhang model for clear waters with the 2SeaColor model for turbid waters would be
411 an ideal approach.

412   **4.3 Variation of K_d maps in Yangtze Estuary**

413   We reproduced the $K_d(490)$ maps from the selected GOCI images acquired on 8 March of 2013
414   using the Zhang model, the Lee model and the 2SeaColor model and the results are presented in Fig.
415   9. We can observe that the $K_d(490)$ maps over the Yangtze Estuary from all three models present
416   the similar patterns in spatial distribution, also shown in previous studies (Shi and Wang, 2010; Shi
417   et al., 2011; Sokoletsky et al., 2014; Wang et al., 2009a). As shown in Fig. 9, results from all three
418   models in clear waters are comparable, but huge differences can be observed in the extremely turbid
419   regions, such as the Hangzhou Bay and North Branch of Yangtze Estuary. The K_d map from the
420   2SeaColor model results in an approximate range from 0.04 to 9.82 m^{-1} (Fig. 9c), while the ranges
421   of $K_d(490)$ from the Zhang model and the Lee model are 0.02 to 3.5 m^{-1} (Fig. 9a) and 0.18 to 12.63
422   m^{-1} (Fig. 9b), respectively. The magnitudes of $K_d(490)$ also vary largely compared to previously
423   reported results for the Yangtze estuary. K_d maps from Shi et al. (2011) and Shi and Wang (2010)
424   are produced from Moderate Resolution Imaging Spectroradiometer (MODIS-Aqua), yielding a
425   range of derived $K_d(490)$ approximately from 0 ~ 4 m^{-1} and from 0 ~ 5 m^{-1} , respectively. The
426   highest $K_d(490)$ even reaches 250 m^{-1} when Sokoletsky et al. (2014) simply calculated $K_d(490)$ as
427   the sum of total absorption and backscattering coefficient.

Fig. 6. K_d maps derived from the GOCI level 2 product (L2P) at wavelength 490 nm using (a) Zhang model, (b) Lee model and (c) 2SeaColor model. The image was captured at 02:16 UTC, 8 March 2013 and 'X' marks are matchup sites.

We compared the field measured $K_d(490)$ with GOCI-derived $K_d(490)$ at six matchup sites for all three models, as presented in Fig. 10. The results are in accordance with the comparison from the Yangtze dataset (Fig. 6c) since the error from the GOCI standard atmospheric correction is acceptable (Fig. 4). The 2SeaColor model ($R^2 = 0.937$ and $\text{RMSE} = 0.317 \text{ m}^{-1}$) is able to provide accurate and stable estimations, while the Zhang model ($R^2 = 0.817$ and $\text{RMSE} = 0.640 \text{ m}^{-1}$) tends to underestimate $K_d(490)$ and the Lee model ($R^2 = 0.927$ and $\text{RMSE} = 2.347 \text{ m}^{-1}$) tends to overestimate $K_d(490)$ for turbid conditions. Note that there are also six data points for the Zhang model in Fig. 10, but two data points overlapped because both the measured and derived values are extremely close. These two matchup sites are geographically close to each other (A6-3 and A6-4 in Fig. 1c).

440

441 **Fig. 7** Comparison between field measured $K_d(490)$ and GOCI-derived $K_d(490)$ using Zhang model, Lee model and
 442 2SeaColor model for the six matchups.

443 As we can see from Fig. 9, all matchup sites are located in clear and medium turbid regions. It is
 444 worth mentioning that field measurements in the extremely turbid regions are absent for model
 445 validation in this study, making validation of derived K_d in extremely turbid water impossible in this
 446 study. However, The $K_d(490)$ range predicted by the 2SeaColor model is in consistent with field
 447 measurements from the East China Sea and Yangtze estuarine waters by Qiu et al. (2013) with K_d
 448 (490) ranging from 0.03 to 10.3 m^{-1} with a mean value of $0.92 \pm 1.59 m^{-1}$. In addition, concentration
 449 of total suspended matter (TSM) in the Hangzhou Bay and the North Branch of Yangtze Estuary is
 450 actually 1 ~ 2 orders of magnitude greater than the one at the matchup sites (Shen et al., 2010),
 451 which should result in a relatively large range of K_d . However, as shown in Fig. 9a, the difference in
 452 K_d derived from the Zhang model is rather small for pixels in the Hangzhou Bay and the two
 453 matchup sites at the top of the image that are considered in medium turbid waters, indicating that
 454 predictions from the Zhang model are underestimated in turbid waters. On the other hand, $K_d(490)$
 455 derived from the Lee model is above 6 m^{-1} in most coastal pixels as shown in Fig. 9b, which is much
 456 larger than the average value reported by Qiu et al. (2013). In accordance with the validation of

457 GOCI-derived K_d as shown in Fig. 10, predictions from the Lee model could be systematically
458 overestimated in medium and extremely waters. Therefore, we argue that the GOCI-derived K_d map
459 from the 2SeaColor model is more reliable, but further validation in extremely turbid waters is still
460 strongly recommended.

461 **5 Conclusions**

462 In this study, we proposed an improvement on the parameterizations in the inverse scheme of the
463 analytical 2SeaColor model. The 2SeaColor model, with improved parametrizations, is able to
464 provide stable and accurate estimations of K_d for wide ranges of water turbidity without the need for
465 tuning coefficients from field measurements. The 2SeaColor model is more appropriate for K_d
466 retrieval in turbid waters compared to the empirical Zhang model and the semi-analytical Lee model.
467 Reasonable K_d maps are also derived when applying the 2SeaColor model to atmosphere corrected
468 GOCI images, reproducing the expected magnitude and range of K_d over the Yangtze Estuary. The
469 successful application of 2SeaColor to GOCI images enables our further study of variations in the
470 K_d distribution at large spatial and temporal scales.

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480 **References**

- 481 Ahn, J.H., Park, Y.J., Ryu, J.H., Lee, B., & Oh, I.S. (2012). Development of Atmospheric Correction
482 Algorithm for Geostationary Ocean Color Imager (GOCI). *Ocean Science Journal*, 47, 247-259
- 483 Ambarwulan, W., Verhoef, W., Mannaerts, C.M., & Salama, M.S. (2012). Estimating total suspended matter
484 concentration in tropical coastal waters of the Berau estuary, Indonesia. *International Journal of Remote*
485 *Sensing*, 33, 4919-4936
- 486 Austin, R.W., & Petzold, T.J. (1981). The determination of the diffuse attenuation coefficient of sea water
487 using the Coastal Zone Color Scanner. *Oceanography from space* (pp. 239-256). New York: Springer
- 488 Babin, M., Morel, A., Fournier-Sicre, V., Fell, F., & Stramski, D. (2003). Light scattering properties of
489 marine particles in coastal and open ocean waters as related to the particle mass concentration. *Limnology*
490 *and Oceanography*, 48, 843-859
- 491 Bergamino, N., Horion, S., Stenuite, S., Cornet, Y., Loisel, S., Plisnier, P.D., & Descy, J.P. (2010). Spatio-
492 temporal dynamics of phytoplankton and primary production in Lake Tanganyika using a MODIS based
493 bio-optical time series. *Remote Sensing of Environment*, 114, 772-780
- 494 Bricaud, A., Morel, A., & Prieur, L. (1981). Absorption by Dissolved Organic-Matter of the Sea (Yellow
495 Substance) in the Uv and Visible Domains. *Limnology and Oceanography*, 26, 43-53
- 496 Chen, J., Cui, T.W., Tang, J.W., & Song, Q.J. (2014). Remote sensing of diffuse attenuation coefficient using
497 MODIS imagery of turbid coastal waters: A case study in Bohai Sea. *Remote Sensing of Environment*, 140,
498 78-93
- 499 Darecki, M., & Stramski, D. (2004). An evaluation of MODIS and SeaWiFS bio-optical algorithms in the
500 Baltic Sea. *Remote Sensing of Environment*, 89, 326-350
- 501 Doron, M., Babin, M., Mangin, A., & Hembise, O. (2007). Estimation of light penetration, and horizontal and
502 vertical visibility in oceanic and coastal waters from surface reflectance. *Journal of Geophysical*
503 *Research-Oceans*, 112
- 504 Duntley, S.Q. (1942). The optical properties of diffusing materials. *Journal of the Optical Society of America*,
505 32, 61--61
- 506 Duntley, S.Q. (1963). Light in the sea. *Journal of the Optical Society of America*, 53, 214--233
- 507 Gordon, H.R., & Wang, M. (1994). Retrieval of water-leaving radiance and aerosol optical thickness over the
508 oceans with SeaWiFS: a preliminary algorithm. *Applied Optics*, 33, 443-452

509 Goyens, C., Jamet, C., & Schroeder, T. (2013). Evaluation of four atmospheric correction algorithms for
510 MODIS-Aqua images over contrasted coastal waters. *Remote Sensing of Environment*, 131, 63-75

511 Hooker, S.B., Lazin, G., Zibordi, G., & McLean, S. (2002). An evaluation of above- and in-water methods
512 for determining water-leaving radiances. *Journal of Atmospheric and Oceanic Technology*, 19, 486-515

513 Hu, C., Feng, L., & Lee, Z. (2012). Evaluation of GOCI sensitivity for at-sensor radiance and GDPS-
514 retrieved chlorophyll-a products. *Ocean Science Journal*, 47, 279-285

515 Hu, C.M., Carder, K.L., & Muller-Karger, F.E. (2000). Atmospheric correction of SeaWiFS imagery over
516 turbid coastal waters: A practical method. *Remote Sensing of Environment*, 74, 195-206

517 IOCCG (2000). Remote Sensing of Ocean Colour in Coastal, and Other Optically-Complex, Waters.
518 Sathyendranath, S. (ed.), *Reports of the International Ocean-Colour Coordinating Group, No.3*, IOCCG,
519 Dartmouth, Canada

520 IOCCG (2006). Remote Sensing of Inherent Optical Properties: Fundamentals, Tests of Algorithms, and
521 Applications. Lee, Z. P. (ed.), *Reports of the International Ocean-Colour Coordinating Group, No. 5*

522 Jamet, C., Loisel, H., & Dessailly, D. (2012). Retrieval of the spectral diffuse attenuation coefficient $K_d(\lambda)$ in
523 open and coastal ocean waters using a neural network inversion. *Journal of Geophysical Research*, 117

524 Kirk, J.T.O. (1984). Dependence of Relationship between Inherent and Apparent Optical-Properties of Water
525 on Solar Altitude. *Limnology and Oceanography*, 29, 350-356

526 Kirk, J.T.O. (1991). Volume Scattering Function, Average Cosines, and the Underwater Light-Field.
527 *Limnology and Oceanography*, 36, 455-467

528 Kirk, J.T.O. (1994). *Light and photosynthesis in aquatic ecosystems*. Cambridge university press

529 Lee, Z., Carder, K.L., Mobley, C.D., Steward, R.G., & Patch, J.S. (1998). Hyperspectral remote sensing for
530 shallow waters. I. A semianalytical model. *Applied Optics*, 37, 6329--6338

531 Lee, Z., Carder, K.L., Mobley, C.D., Steward, R.G., & Patch, J.S. (1999). Hyperspectral remote sensing for
532 shallow waters. 2. Deriving bottom depths and water properties by optimization. *Applied Optics*, 38, 3831-
533 -3843

534 Lee, Z., Hu, C., Shang, S., Du, K., Lewis, M., Arnone, R., & Brewin, R. (2013). Penetration of UV-visible
535 solar radiation in the global oceans: Insights from ocean color remote sensing. *Journal of Geophysical*
536 *Research: Oceans*, 118, 4241-4255

537 Lee, Z., Lance, V.P., Shang, S.L., Vaillancourt, R., Freeman, S., Lubac, B., Hargreaves, B.R., Del Castillo, C.,
538 Miller, R., Twardowski, M., & Wei, G.M. (2011). An assessment of optical properties and primary
539 production derived from remote sensing in the Southern Ocean (SO GasEx). *Journal of Geophysical*
540 *Research-Oceans*, 116

541 Lee, Z., Weidemann, A., Kindle, J., Arnone, R., Carder, K.L., & Davis, C. (2007). Euphotic zone depth: Its
542 derivation and implication to ocean-color remote sensing. *Journal of Geophysical Research-Oceans*, 112,
543 C03009

544 Lee, Z.P., Carder, K.L., & Arnone, R.A. (2002). Deriving inherent optical properties from water color: a
545 multiband quasi-analytical algorithm for optically deep waters. *Applied Optics*, 41, 5755--5772

546 Lee, Z.P., Darecki, M., Carder, K.L., Davis, C.O., Stramski, D., & Rhea, W.J. (2005a). Diffuse attenuation
547 coefficient of downwelling irradiance: An evaluation of remote sensing methods. *Journal of Geophysical*
548 *Research-Oceans*, 110

549 Lee, Z.P., Du, K.P., & Arnone, R. (2005b). A model for the diffuse attenuation coefficient of downwelling
550 irradiance. *Journal of Geophysical Research-Oceans*, 110

551 Loiselle, S.A., Bracchini, L., Cozar, A., Dattilo, A.M., Tognazzi, A., & Rossi, C. (2009). Variability in
552 photobleaching yields and their related impacts on optical conditions in subtropical lakes. *Journal of*
553 *Photochemistry and Photobiology B: Biology*, 95, 129-137

554 Majozzi, N.P., Salama, M.S., Bernard, S., Harper, D.M., & Habte, M.G. (2014). Remote sensing of euphotic
555 depth in shallow tropical inland waters of Lake Naivasha using MERIS data. *Remote Sensing of*
556 *Environment*, 148, 178-189

557 McClain, C.R., Arrigo, K., Tai, K.S., & Turk, D. (1996). Observations and simulations of physical and
558 biological processes at ocean weather station P, 1951–1980. *Journal of Geophysical Research: Oceans*
559 (1978–2012), 101, 3697-3713

560 Mitchell, C., Cunningham, A., & McKee, D. (2014). Remote sensing of shelf sea optical properties:
561 Evaluation of a quasi-analytical approach for the Irish Sea. *Remote Sensing of Environment*, 143, 142-153

562 Mobley, C.D. (1994). *Light and water : radiative transfer in natural waters*. Academic press San Diego

563 Mobley, C.D. (1999). Estimation of the remote-sensing reflectance from above-surface measurements.
564 *Applied Optics*, 38, 7442-7455

565 Morel, A. (1974). Optical properties of pure water and pure sea water. *Optical aspects of oceanography*, 1-24

566 Morel, A., & Loisel, H. (1998). Apparent optical properties of oceanic water: dependence on the molecular
567 scattering contribution. *Applied Optics*, 37, 4765-4776

568 Morel, A.E., & Gentili, B. (1993). Diffuse reflectance of oceanic waters. II Bidirectional aspects. *Applied*
569 *Optics*, 32, 6864--6879

570 Mueller, J.L. (2000). SeaWiFS algorithm for the diffuse attenuation coefficient, K (490), using water-leaving
571 radiances at 490 and 555 nm. *SeaWiFS postlaunch calibration and validation analyses, part (p. 24)*

572 Nordkvist, K., Loisel, H., & Gaurier, L.D. (2009). Cloud masking of SeaWiFS images over coastal waters
573 using spectral variability. *Optics Express*, 17, 12246-12258

574 Qiu, Z., Wu, T., & Su, Y. (2013). Retrieval of diffuse attenuation coefficient in the China seas from surface
575 reflectance. *Optics Express*, 21, 15287-15297

576 Röttgers, R., & Gehnke, S. (2011). Measurement of light absorption by aquatic particles: improvement of the
577 quantitative filter technique by use of an integrating sphere approach. *Applied Optics*, 51, 1336-1351

578 Ruddick, K.G., De Cauwer, V., Park, Y.-J., & Moore, G. (2006). Seaborne measurements of near infrared
579 water-leaving reflectance: The similarity spectrum for turbid waters. *Limnology and Oceanography*, 51,
580 1167-1179

581 Ruddick, K.G., Ovidio, F., & Rijkeboer, M. (2000). Atmospheric correction of SeaWiFS imagery for turbid
582 coastal and inland waters. *Applied Optics*, 39, 897-912

583 Ryu, J.H., Han, H.J., Cho, S., Park, Y.J., & Ahn, Y.H. (2012). Overview of Geostationary Ocean Color
584 Imager (GOCI) and GOCI Data Processing System (GDPS). *Ocean Science Journal*, 47, 223-233

585 Salama, M.S., Melin, F., & Van der Velde, R. (2011). Ensemble uncertainty of inherent optical properties.
586 *Optics Express*, 19, 16772-16783

587 Salama, M.S., Monbaliu, J., & Coppin, P. (2004). Atmospheric correction of Advanced Very High
588 Resolution Radiometer imagery. *International Journal of Remote Sensing*, 25, 1349-1355

589 Salama, M.S., & Shen, F. (2010a). Simultaneous atmospheric correction and quantification of suspended
590 particulate matters from orbital and geostationary earth observation sensors. *Estuarine Coastal and Shelf
591 Science*, 86, 499-511

592 Salama, M.S., & Shen, F. (2010b). Stochastic inversion of ocean color data using the cross-entropy method.
593 *Optics Express*, 18, 479-499

594 Salama, M.S., & Stein, A. (2009). Error decomposition and estimation of inherent optical properties. *Applied
595 Optics*, 48, 4947-4962

596 Salama, M.S., & Verhoef, W. (2015). Two-stream remote sensing model for water quality mapping:
597 2SeaColor. *Remote Sensing of Environment*, 157, 111-122

598 Sathyendranath, S., Cota, G., Stuart, V., Maass, H., & Platt, T. (2001). Remote sensing of phytoplankton
599 pigments: a comparison of empirical and theoretical approaches. *International Journal of Remote Sensing*,
600 22, 249-273

601 Shen, F., & Verhoef, W. (2010). Suppression of local haze variations in MERIS images over turbid coastal
602 waters for retrieval of suspended sediment concentration. *Optics Express*, 18, 12653-12662

603 Shen, F., Verhoef, W., Zhou, Y.X., Salama, M.S., & Liu, X.L. (2010). Satellite Estimates of Wide-Range
604 Suspended Sediment Concentrations in Changjiang (Yangtze) Estuary Using MERIS Data. *Estuaries and
605 Coasts*, 33, 1420-1429

606 Shen, F., Zhou, Y.X., Li, J.F., He, Q., & Verhoef, W. (2013). Remotely sensed variability of the suspended
607 sediment concentration and its response to decreased river discharge in the Yangtze estuary and adjacent
608 coast. *Continental Shelf Research*, 69, 52-61

609 Shen, F., Zhou, Y.X., Peng, X.Y., & Chen, Y.L. (2014). Satellite multi-sensor mapping of suspended
610 particulate matter in turbid estuarine and coastal ocean, China. *International Journal of Remote Sensing*,
611 35, 4173-4192

612 Shi, W., & Wang, M. (2010). Satellite observations of the seasonal sediment plume in central East China Sea.
613 *Journal of Marine Systems*, 82, 280-285

614 Shi, W., Wang, M.H., & Jiang, L.D. (2011). Spring-neap tidal effects on satellite ocean color observations in
615 the Bohai Sea, Yellow Sea, and East China Sea. *Journal of Geophysical Research-Oceans*, 116

616 Smith, R.C., & Baker, K.S. (1978). Optical classification of natural waters. *Limnology and Oceanography*, 23,
617 260-267

618 Smith, R.C., & Baker, K.S. (1981). Optical properties of the clearest natural waters (200-800 nm). *Applied*
619 *Optics*, 20, 177-184

620 Sokoletsky, L., Yang, X., & Shen, F. (2014). MODIS-based retrieval of suspended sediment concentration
621 and diffuse attenuation coefficient in Chinese estuarine and coastal waters. In, *SPIE Asia Pacific Remote*
622 *Sensing* (pp. 926119-926119-926125): International Society for Optics and Photonics

623 Sokoletsky, L.G., & Shen, F. (2014). Optical closure for remote-sensing reflectance based on accurate
624 radiative transfer approximations: the case of the Changjiang (Yangtze) River Estuary and its adjacent
625 coastal area, China. *International Journal of Remote Sensing*, 35, 4193-4224

626 Stramska, M., & Zuzewicz, A. (2013). Influence of the parametrization of water optical properties on the
627 modelled sea surface temperature in the Baltic Sea. *Oceanologia*, 55, 53-76

628 Sun, D.Y., Qiu, Z.F., Li, Y.M., Shi, K., Huang, C.C., & Gong, S.Q. (2014). New strategy to improve
629 estimation of diffuse attenuation coefficient for highly turbid inland waters. *International Journal of*
630 *Remote Sensing*, 35, 3350-3371

631 Wang, M., & Shi, W. (2007). The NIR-SWIR combined atmospheric correction approach for MODIS ocean
632 color data processing. *Optics Express*, 15, 15722-15733

633 Wang, M.H., Son, S., & Harding, L.W. (2009a). Retrieval of diffuse attenuation coefficient in the
634 Chesapeake Bay and turbid ocean regions for satellite ocean color applications. *Journal of Geophysical*
635 *Research-Oceans*, 114

636 Wang, M.H., Son, S., & Shi, W. (2009b). Evaluation of MODIS SWIR and NIR-SWIR atmospheric
637 correction algorithms using SeaBASS data. *Remote Sensing of Environment*, 113, 635-644

638 Werdell, P.J., & Bailey, S.W. (2005). An improved in-situ bio-optical data set for ocean color algorithm
639 development and satellite data product validation. *Remote Sensing of Environment*, 98, 122-140

640 Wu, Y., Tang, C.C.L., Sathyendranath, S., & Platt, T. (2007). The impact of bio-optical heating on the
641 properties of the upper ocean: A sensitivity study using a 3-D circulation model for the Labrador Sea.
642 *Deep Sea Research Part II: Topical Studies in Oceanography*, 54, 2630-2642

643 Zhang, T., & Fell, F. (2007). An empirical algorithm for determining the diffuse attenuation coefficient K-d
644 in clear and turbid waters from spectral remote sensing reflectance. *Limnology and Oceanography-*
645 *Methods*, 5, 457-462

646 Zhang, Y.L., Qin, B.Q., Zhu, G.W., Gao, G., Luo, L.C., & Chen, W.M. (2006). Effect of sediment
647 resuspension on underwater light field in shallow lakes in the middle and lower reaches of the Yangtze
648 River: A case study in Longgan Lake and Taihu Lake. *Science in China Series D-Earth Sciences*, 49, 114-
649 125

650 Zibordi, G., Mélin, F., Berthon, J.-F., Holben, B., Slutsker, I., Giles, D., D'Alimonte, D., Vandemark, D.,
651 Feng, H., & Schuster, G. (2009). AERONET-OC: a network for the validation of ocean color primary
652 products. *Journal of Atmospheric and Oceanic Technology*, 26, 1634-1651

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Figure 1

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Figure 4

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Figure 6

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Figure 9

Figure 10