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Modern approaches to shipborne ocean color remote sensing
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1 Modern approaches to shipborne ocean color remote sensing

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12 In this work, modernized shipborne ocean color remote sensing procedures are discussed. For collection
13 of high resolution radiometric quantities a setup of five radiometers and a bidirectional camera system,
14 providing panoramic sea surface and sky images, is proposed. Visual inspection of camera images is
15 utilized as a supporting qualitative verification tool for measured radiometric quantities before calculating
16 ocean color products e.g. water leaving radiance and remote sensing reflectance (R_{RS}). A peak around
17 R_{RS} (760 nm) was observed in spectra affected by relatively high surface reflected glint (SRG) which
18 suggests this waveband could be a useful SRG indicator. Simplified steps applicable to computing
19 uncertainties in SRG corrected R_{RS} are proposed and discussed. The possibility of utilizing ‘un-weighted
20 multi-model averaging’ to determine the ‘best approximation R_{RS} ’, which is the average of four or more
21 common SRG correction models is examined. This ‘best approximation R_{RS} ’ provides an estimate of R_{RS}
22 based on assumptions derived from several radiative transfer simulations and field investigations. It is
23 important to consider that, applying the average R_{RS} strongly depends on user needs such as spectra
24 intensity, shape, or band ratio in inferring optically active water constituents. However, applying the
25 average R_{RS} is anticipated to mitigate the uncertainties or biases that result from user inherent subjective
26 choice of a particular SRG correction model. Comparisons between in-water and above-water
27 observations are used to assess the extent of applicability of SRG multi-model averaging. Correlations
28 among standard SRG models were tested to determine degree of association or similarities in the SRG
29 models. It is suggested that uncertainty in the ‘best approximation R_{RS} ’ be determined by the unbiased
30 percent difference between the highest and the lowest SRG corrected R_{RS} from the four or widely used
31 approaches. Findings and proposals in this work are aimed at contributing towards uniform and traceable
32 methodology to determine shipborne R_{RS} and its errors to ensure comparability with future investigations.
33 The ocean color community is also encouraged to publish radiometric field measurements with matching
34 metadata in open access databases.

35

36 1.Introduction

37 Remote sensing reflectance (R_{RS}) is an important ocean color remote sensing end-product used to infer
38 optically active water constituents linked to climate change which has seen it gain the name essential
39 climate variable (GCOS, 2011; IOCCG, 2008). To determine R_{RS} Eq. (1) is widely implemented

$$41 \quad R_{RS} = \frac{L_T - L_{SR}}{E_D} = \frac{L_T - (\rho \times L_{sky} + R)}{E_D} \quad (1)$$

42
43 where $L_T(\theta_T, \Phi, \lambda)$ is the total upwelling sea surface radiance, $E_D(\lambda)$ is total downwelling irradiance, L_{sky}
44 is the sky leaving radiance and $L_{SR}(\theta, \Phi, \lambda)$ is the surface reflected glint (SRG). L_{SR} consists of a fraction
45 ($\rho \approx 0.02 - 0.05$) of the sky reflected light and R which is an approximation of sun glint, residual glint,
46 whitecaps, and foam reflected light (Garaba and Zielinski, 2013c; Moore, 1980; Olszewski and Darecki,
47 1999; Yan and Sydor, 2006). At present it is not possible fully quantify all components of L_{SR} especially R
48 however most SRG approaches are assumed to provide a best approximate of R_{RS} .

49
50 Handling of SRG in shipborne ocean color remote sensing is rather naturally subjective, as no correction
51 method has been widely preferred in all water bodies (Garaba and Zielinski, 2013c; Hooker et al., 2002).
52 The absence of a standard SRG technique to determine corrected radiometric quantities makes it very
53 challenging to compare observations from numerous shipborne remote sensing studies. The problems in
54 comparing observations arise from different investigations using various (i) sensor geometry i.e. nadir-
55 zenith angle and relative azimuthal angle of sensors to the sun, (ii) little or no available/recorded
56 additional important information about sea state and cloud conditions, (iii) optical sensor sensitivity as
57 well as traceable calibration of sensors, and (iv) observations during non-optimal sea and sky conditions
58 (Garaba and Zielinski, 2013c; Hooker et al., 2002; Lee et al., 2014). Issues (i) and (ii) are steps well
59 defined in standard protocols for shipborne remote sensing (Mobley, 1999; Mueller et al., 2003; Toole et
60 al., 2000). Despite all these recommended steps, some shipborne remote sensing investigations seem
61 not to report the metadata as they do not record the metadata or maybe record the metadata but do not
62 report the metadata in their work. Furthermore, the SRG correction approaches widely used were
63 developed using a rather limited set of in-situ observations and thus tend to rely on assumptions that
64 might not accurately represent the field observations from different regions and environmental conditions
65 (Garaba and Zielinski, 2013c). For these reasons, there is a likelihood of errors and uncertainties that
66 needs to be traceable and verified in ocean color remote sensing.

67
68 Additional steps have also been proposed to mitigate the effects of SRG or L_{SR} contamination in
69 shipborne remote sensing such as (i) collecting measurements at azimuthal angles 90 - 135 ° relative to
70 the sun aimed at reducing possible contamination from ship shadow (Mueller et al., 2003), (ii) directly

71 measuring water leaving radiance just below the sea surface at over the side stations with domed cover
72 attached to a radiance radiometer which eliminates the need for SRG correction (Tanaka et al., 2006),
73 (iii) profiling light within the water column and extrapolating the measured quantities to the sea surface at
74 over the side stations (Hooker et al., 2002), (iv) polarization techniques (Fougnie et al., 1999; Harmel et
75 al., 2012; Yan and Sydor, 2006) and (v) statistical time series analysis of measurements (Olszewski and
76 Kowalczyk, 2000). Despite all these proposed techniques, the ocean color community still endeavors to
77 reach a common approach. Among the hurdles are instrument costs and availability, lack of uncertainty
78 analysis, shipborne time, and expertise of persons obtaining measurements.

79
80 One technique that has not been fully utilized in ocean color SRG correction models is the use of multi-
81 model averaging. Multi-model averaging has been used to predict variables both in social and natural
82 sciences predictive models for decades (Barnard, 1963; Hoeting et al., 1999; Nakagawa and Freckleton,
83 2011). Moreover, statisticians suggest that multi-model averaging improves uncertainty analysis like
84 biases and minimizes the risk of overconfident conclusions arising from using a single model (Draper,
85 1995; Hodges, 1987; Hoeting et al., 1999). Applying the multi-model average also benefits from the fact
86 that all the SRG correction models are based on near homogenous assumptions used in radiative
87 transfer simulations (e.g. wind speed, cloud cover, cloud type, optically active water components, light
88 distribution, sensor geometry) theories as well as field observations that tend to overlap and therefore
89 share some consistencies as explained in detail by a recent review (Garaba and Zielinski, 2013c). These
90 scenarios and the extent of overlap are in a way similar to those found in e.g. Intergovernmental Panel on
91 Climate Change models which makes multi-model averaging in determining ocean color products
92 suitable. However, it is also important that users take care when applying the average R_{RS} as it might
93 affect their bio-optical algorithms which might depend on spectra shape, intensity or band ratio.

94
95 In this work we aim to expand on a recent review on methods of reducing SRG in shipborne remote
96 sensing (Garaba and Zielinski, 2013c), by proposing modern approaches with special focus on
97 uncertainty analysis that can be easily implemented in shipborne ocean color remote sensing
98 observations. The possibility of multi-model averaging of standard SRG correction models is examined
99 and discussed using sample field measurements. Part of this study is to contribute towards a growing
100 need for a common generic SRG approach to determine R_{RS} and its associated uncertainties, for
101 instance there is an increasing number of investigations related to understanding ocean color product
102 similarities, dependencies, and uncertainties (de Moraes Rudorff et al., 2014; Lee et al., 2014; Wang et
103 al., 2005). Additionally, an improved sensor setup is proposed and its suitability in future shipborne ocean
104 color remote sensing is discussed.

106 2. Data and methods

107 2.1 Camera system and radiometer setup

108 To collect panoramic sea surface and sky images a commercially available security camera Mobotix
109 DualDome D12 equipped with two L43 lenses with 45° horizontal perspective is used. The system is
110 fixed at the ships rail directly above the bridge room (Fig. 1). With the new setup the camera provides a
111 near panoramic view of the sea and sky. Acquisition of images is synchronized with the radiometer
112 measurements. A set of 5 TriOS RAMSES radiometers is implemented at the top of the foremast; one
113 ACC hyperspectral cosine irradiance meter and four ARC hyperspectral radiance meters with 7° field-of-
114 view in air. The RAMSES-ACC hyperspectral cosine irradiance meter is used to measure the total
115 downwelling irradiance $E_D(\lambda)$. Two RAMSES-ARC meters are positioned at a nadir angle of 45° facing
116 the sea surface to measure the total upwelling sea surface radiance $L_T(\theta_T, \Phi, \lambda)$ with a relative azimuthal
117 angle between them of 90°. The other two RAMSES-ARC meters with same relative azimuthal angle of
118 90°, are positioned at a zenith angle of 45° facing the sky to measure the sky leaving radiance $L_{sky}(\theta_{sky},$
119 $\Phi, \lambda)$. A more detailed schematic of the radiometer platform is shown in Fig. 2.

120 121 2.2 Beam attenuation and absorption measurements

122 Underway measurements of beam attenuation and absorption coefficient of sample water were
123 performed using a WETlabs AC-9 meter in flow-through mode. Sample water from a depth of about 4 m
124 was continuously pumped through a custom made Pocket-FerryBox (4H-Jena, Germany) which
125 measured standard oceanographic parameters (practical salinity, temperature, chl-a fluorescence) and
126 passed on to the AC-9.

127
128 Beam attenuation and absorption coefficient measurement were filtered using a running median to
129 eliminate effects of bubbles. The measurements were corrected for temperature and salinity effects using
130 the data obtained with the FerryBox-system and the coefficients published in Pegau et al. (1997).
131 Instrument calibration was carried out at regular intervals using purified water. To account for light
132 scattering effects, the absorption data were corrected using a modern approach (Röttgers et al., 2013).
133 By visual inspection of the data, one of the absorption channels (630 nm) provided measurements which
134 were qualitatively reasonable but relatively too high with respects to the other neighboring channels. For
135 this reason, the data of this channel were omitted from the analysis. Beam attenuation and absorption
136 coefficients were converted into above water remote sensing reflectance (R_{rs}) using Eq. (2)

$$137$$
$$138 R_{rs} = T \times \frac{f}{Q} \times \frac{b_{Total}}{a_{Total} + b_{Total}} \quad (2)$$
$$139$$

140 Where $T = 0.52$ is the reflection and refraction components of the water surface and $f/Q = 0.13$ is the
141 bidirectional component of light (Loisel and Morel, 2001). The AC-9 bandwidth data is centered over a 10
142 nm window and therefore the above water R_{RS} is also centered to match this bandwidth.

143

144 **2.2 Calculating R_{RS} uncertainty**

145 A revised protocol and review of SRG correction models suggests the use of several approaches. It
146 proposes a set of objective steps for selecting an appropriate correction (Garaba and Zielinski, 2013c).
147 To determine the best R_{RS} this selection can be tedious and does not provide any uncertainties in the end
148 product R_{RS} . We therefore suggest obtaining uncertainty in R_{RS} [sr^{-1}] at distinct wavelengths by using
149 unbiased percent difference (*UPD*) in Eq. (2)

150

$$151 \quad UPD[\%] = \frac{|X_{\min} - X_{\max}|}{0.5 \times (X_{\min} + X_{\max})} \times 100 \quad (2)$$

152

153 where X_{\max} is the highest R_{RS} spectra and X_{\min} is the lowest R_{RS} spectra after SRG correction. *UPD*
154 provides the uncertainty between two observations from which the correct one is unknown. Use of *UPD*
155 is considered appropriate here because it provides an unbiased comparison quantification of the
156 difference between the least corrected – highest signal and most corrected – lowest signal. Furthermore,
157 *UPD* provides a relative uncertainty or error comparison quantity that has been used for both practical
158 and theoretical applications in social and natural sciences (Makridakis, 1993).

159

160 To apply this statistical parameter to remote sensing, the R_{RS} is determined by the four main surface
161 reflected glint correction models (Gould et al., 2001; Lee et al., 2010; Mobley, 1999; Ruddick et al.,
162 2006). Hereon these models will be referred to as M99, G01, R06, and L10; the first letter represents the
163 author and the year of publication. To mitigate the challenge that arise from subjectivity or justifying use
164 of a particular approach as reported (Garaba et al., 2014a; Garaba et al., 2014b; Garaba and Zielinski,
165 2013a), the multi-model average of these four approaches will therefore be the ‘best approximation R_{RS} ’
166 reported as in Eq. (3)

167

$$168 \quad R_{RS} [sr^{-1}] \Rightarrow X_{mean} (X_{\min}, X_{\max}) \quad (3)$$

169

170 where X_{mean} is the multi-model average R_{RS} , X_{min} is the minimum and X_{max} is the maximum R_{RS}
171 determined by one of the four models. Therefore the uncertainty at a particular wavelength ‘best
172 approximation R_{RS} ’ is the *UPD* computed in Eq. (2). An additional parameter to determine the maximum
173 error (ΔX_{\max}) will be evaluated using Eq. (4),

174

175 $\Delta X_{\max} [sr^{-1}] = 0.5 \times (X_{\max} - X_{\min})$ (4)
 176 $\Rightarrow X_{mean} \pm \Delta X_{\max}$

176

177 Uncertainty between above-water and in-water derive $R_{RS}(X)$ was computed from mean absolute
 178 percent difference (*MAPD*) and mean percent difference (*MPD*). *MAPD* Eq. (5) and *MPD* from Eq. (6) are
 179 measures of scatter and bias respectively.

180

181 $MAPD[\%] = 100 * \frac{1}{N} \sum_{i=1}^N \frac{|X_{above-water} - X_{in-water}|}{X_{in-water}}$ (5)

182

183 $MPD[\%] = 100 * \frac{1}{N} \sum_{i=1}^N \frac{X_{above-water} - X_{in-water}}{X_{in-water}}$ (6)

184

185 3. Results and discussion

186 3.1 Camera and spectra features

187 Onboard R/V Heincke the new camera system provides a near panoramic view of the sea surface and
 188 sky region matching the radiometric observations. The radiometers are located at the top of the foremast
 189 directly in front of the camera system. The goal of taking radiometric measurements at azimuthal angles
 190 of 90 - 135 ° relative to the sun is to reduce the surface reflected glint contamination. Based on our
 191 camera image inspection, at any time the azimuthal angle between the sea surface facing radiometers
 192 guarantees that one of the radiometers is at least targeted at a sea surface region with little or minimal
 193 visible glitter. An example of images with calculated R_{RS} spectra are shown in Fig. 3. The apparent glint
 194 or glitter is observed in the right (starboard) image of Fig. 3, little or minimal visible glitter can be
 195 observed in the left (portside) image. Corresponding calculated R_{RS} spectra on the right (starboard) side
 196 is relatively high over the measured spectrum based on the SGR by M99 and R06. It is however high
 197 only in the green spectrum and around 760 nm for the SGR corrected spectra by G01 and L10. To
 198 examine this we look at the correlations in the next section.

199

200 A unique feature was observed in all spectra and is highlighted (Fig. 4). At the R_{RS} wavelength range 750
 201 – 780 nm it was noted that in the presence of sun glitter there is a peak right (starboard) side while in the
 202 absence of glitter the signal is nearly flat left (portside). These wavebands around 760 nm have been
 203 shown to be associated with oxygen absorption and to some degree related to glint (Kutser et al., 2009).
 204 In this work we presume that this feature might be an artifact or could also be attributed to a
 205 characteristic of the oxygen signature that is related to surface reflected glint. It is proposed that more
 206 work should consider this band as a proxy for sunglint presence.

207 **3.2 Negative R_{RS}**

208 The aspect of negative R_{RS} spectra is of major concern in the ocean color community (Garaba and
209 Zielinski, 2013c; Olszewski and Darecki, 1999; Yan and Sydor, 2006). In a case study sources of
210 negative spectra were investigated and found out that the negative spectra arise from assuming a flat
211 water surface or using Fresnel reflectance in SRG correction (Yan and Sydor, 2006). Yan and Sydor
212 (Yan and Sydor, 2006) further illustrate the influence of colored dissolved organic material in
213 approximating R_{RS} which can lead to false negative values. In their work they also suggest that waters
214 with back scattering coefficient : absorption coefficient of yellow substance at 400 nm less than 1 will
215 produce negative R_{RS} . The root cause of negative spectra lies in the SRG correction, therefore users
216 ought to be careful when applying any particular correction method. In most cases when you have
217 negative values in G01 you are likely to have negative values in L10 because these two models assume
218 Fresnel reflectance but they slightly vary in the magnitude of residual glint they generate. The M99 use a
219 reflectance factor of 0.028 whilst R06 varies depending on cloud cover and wind speed. It is
220 recommended to omit negative values in any ocean color information analysis.

221 222 **3.3 Uncertainties at individual wavebands and band ratio**

223 Goals of this section are to compare the different surface reflected correction models and evaluate the
224 use of the multi model R_{RS} , we look at the R_{RS} at 440, 488, 555, 676 and 730 nm as well as the band
225 ratio 488/555 nm. These wavebands are widely used in classic predictive algorithms and for comparison
226 tasks (de Moraes Rudorff et al., 2014; Garaba et al., 2014b; Garaba and Zielinski, 2013a; Wang et al.,
227 2005). A total of 943 above-water and in-water measurements were collected underway in the North Sea
228 aboard R/V Sonne in September 2014. These measurements were matched according to time of
229 measurement. Above-water measurements were collected at 5 minute intervals whilst the in-water at 1
230 minute intervals. In-water AC-9 information was then averaged to ± 2 minutes matching the above-water
231 information. Uncertainties in the measurements (Table 1) were determined using Eq. (5) and Eq. (6).

232
233 At each wavelength investigated in Table 1 it is observed that the bias and scatter of SRG corrected
234 information is variable. For example at 440 nm L10 provides minimal bias or MPD (3 ± 47) % but at 488
235 nm G01 provides better statistics MPD (0 ± 42) % and for the band ratio 488/555 the average of all
236 models provides better statistics. Based on our dataset when applying band ratio the average of SRG
237 corrected spectra has minimal uncertainties but at individual wavebands each SRG model has varying
238 uncertainties relative to in-water observations. Average bias or MPD was generally less than 25 % and
239 scatter MAPD was less than 50 %. We assume these are moderate uncertainties for underway
240 observations considering that environmental perturbations arise from rough sea surface conditions, wind
241 speed and cloud cover.

242

243 **3.4 Correlation tests among SRG models**

244 We applied Spearman's rank-order correlation test to determine the degree of association among the
245 models. Spearman's rank-order correlation test was applied because the dataset was determined to be
246 of non-normal distribution based on Shapiro-Wilk's parametric hypothesis test. A total of 2152
247 measurements from high latitude melt waters and fjordal waters as well as northwestern European shelf
248 seas were analyzed here. These observations are available on request and some are available in open
249 access form via the PANGAEA online database (Garaba et al., 2011; Garaba and Zielinski, 2013b). For
250 brevity we only check for Spearman correlations in the blue (440 nm) Fig. 5, green (555 nm) Fig. 6, red
251 (715 nm) Fig. 7 and the band ratio (490/555 nm) Fig. 8. Negative values are eliminated in the analysis
252 stage and in MathWorks Matlab 2014a they are set to NaN. Spearman correlation statistics are
253 presented in Fig. 5 – Fig. 8.

254

255 Spearman correlations in the blue spectrum at 440 nm show that all SRG models excluding the average
256 had very weak to very strong positive significant associations among themselves, whilst average of the
257 SRG models had moderate to very strong significant associations with all models. The green spectrum at
258 555 nm show that all SRG models excluding the average had weak to very strong positive significant
259 associations among themselves, whilst average of the SRG models had strong to very strong significant
260 associations with all models. The red spectrum at 715 nm show that all SRG models excluding the
261 average had very weak to very strong positive significant associations among themselves, whilst average
262 of the SRG models had moderate to very strong significant associations with all models. Band ratio
263 (490/555) nm had in general very strong significant associations for all SRG models and the average of
264 these models. These correlation statistics suggest that the SRG models tested here share some
265 statistically significant similarities of varying degrees of association, with very strong significant
266 correlations between G01 and L10 as well as M99 and R06. The positive significant associations
267 determined here are consistent with our assumption, the SRG correction models are based on common
268 assumptions used in radiative transfer simulations, theories as well as field observations that tend to
269 overlap and are therefore analogous (Garaba and Zielinski, 2013c).

270

271 **3.5 Reporting R_{RS} and its uncertainties**

272 Using the herein proposed method, visualization of R_{RS} information can be done as shown Fig. 9. It
273 indicates the average of the four widely used surface reflected glint correction models (Gould et al., 2001;
274 Lee et al., 2010; Mobley, 1999; Ruddick et al., 2006), the range is represented by the maximum and
275 minimum value at each wavelength. Furthermore to numerically present the R_{RS} , Table 2 gives a
276 summary of the information shown in Fig. 9. Although the example provided in Table 1 shows low
277 uncertainties it also provides a way future could present there measurements.

278

279

280 **4. Conclusions and Outlook**

281 There are continuing efforts to develop ocean color remote sensing algorithms that are applicable in most
282 water types, with room for improvement, for example to determine inherent optical properties of water
283 GIOP (Werdell et al., 2013). However, in shipborne ocean color remote sensing the challenge of
284 contamination in observations by environmental perturbations namely wind-roughened sea surface
285 contributing to sun glitter and meteorological conditions affects both accuracy and efforts of coming up
286 with common generic methods.

287

288 A generic SRG model for shipborne remote sensing is needed due to limited conformity in field
289 observations. Nevertheless, as a recent work summarizes the challenge in developing generic
290 approaches will remain regional and measurement specific (Lee et al., 2014). For example in computing
291 remote sensing reflectance (R_{RS}) from IOPs errors can arise from use of f/Q which is variable ranging
292 between 0.08 – 0.14 and T the reflection and refraction component of water ranging between 0.52 – 0.54
293 (Aurin and Dierssen, 2012; Li et al., 2013; Loisel and Morel, 2001; Morel and Gentili, 1996). Such flexible
294 variables are an indication that finding a superior model in ocean color remote sensing is complicated but
295 we have to make the best of what we know as well as what field observations and model simulations
296 confirm.

297

298 To this end, in this paper we present a modern approach that is reasonably appropriate for automated
299 continuous measurements in shipborne remote sensing. It takes advantage of the commercially available
300 hyperspectral radiometers combined with a camera system for qualitative analysis. In addition, a simple
301 multi-model average SRG correction for remote sensing reflectance (R_{RS}) approach is proposed. Field
302 observations are used to evaluate the usefulness of applying a multi-model averaged R_{RS} in estimating
303 ocean color products. Findings based on used datasets show that to some degree multi-model averaged
304 R_{RS} is reasonably suited for ocean color remote sensing and end-product derivation. Spearman
305 correlation tests confirm our assumption that these four SRG correction models share similarities in there
306 algorithms with very strong significant correlations between G01 and L10 as well as M99 and L06.

307

308 The study still has some questions that need to be considered in future investigations; (i) if a surface
309 reflected glint correction approach produces a negative spectrum does it mean the waveband of interest
310 even if positive is wrong?, (ii) is the $\pm 5\%$ uncertainty threshold in ocean color applicable when the
311 average of various surface reflected glint correction models is used?, and (iii) what uncertainty or
312 unbiased percent difference threshold would be sufficient to justify use of ‘un-weighted multi-model
313 averaging’? In this work we aim to show a need to have a uniform and traceable methodology to
314 determine R_{RS} and its errors to ensure comparability to future investigations. We also strongly encourage

315 the ocean color community to submit further field measurements and sufficient matching metadata to
316 open access online repositories like PANGAEA (<http://www.pangaea.de/>) or SeaBASS
317 (<http://seabass.gsfc.nasa.gov/>).

318

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323

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436 **Table 1** Statistical results from comparison analysis between in-water derived remote sensing reflectance
 437 (R_{RS}) and above-water derived R_{RS} . M(A)PD is the mean (absolute) percent difference \pm standard
 438 deviation.

Wavelength [nm]	M99	G01	R06	L10	Average
440 - MPD	-24 \pm 47	-9 \pm 45	-25 \pm 48	3 \pm 47	-25 \pm 45
440 - MAPD	48 \pm 21	40 \pm 22	49 \pm 21	40 \pm 24	46 \pm 22
488 - MPD	-9 \pm 44	0 \pm 42	-8 \pm 44	3 \pm 48	-14 \pm 46
488 - MAPD	39 \pm 22	36 \pm 20	39 \pm 22	42 \pm 23	42 \pm 22
555 - MPD	-12 \pm 43	5 \pm 45	-12 \pm 44	-1 \pm 45	-2 \pm 48
555 - MAPD	40 \pm 21	39 \pm 23	40 \pm 21	38 \pm 24	42 \pm 22
676 - MPD	-8 \pm 43	8 \pm 39	-8 \pm 42	-10 \pm 43	-10 \pm 44
676 - MAPD	37 \pm 22	34 \pm 21	37 \pm 22	39 \pm 20	39 \pm 23
715 - MPD	-18 \pm 44	8 \pm 42	-19 \pm 43	-4 \pm 41	-5 \pm 45
715 - MAPD	42 \pm 22	36 \pm 21	41 \pm 22	35 \pm 21	41 \pm 20
488/555 - MPD	-7 \pm 32	6 \pm 35	-6 \pm 34	6 \pm 36	3 \pm 32
488/555 - MAPD	24 \pm 22	29 \pm 21	27 \pm 22	30 \pm 22	26 \pm 20

439

440

441 Table 2 Remote sensing reflectance (R_{RS}) on 12 March 2013 at 10:00 from the port side aboard R/V
 442 Heincke.

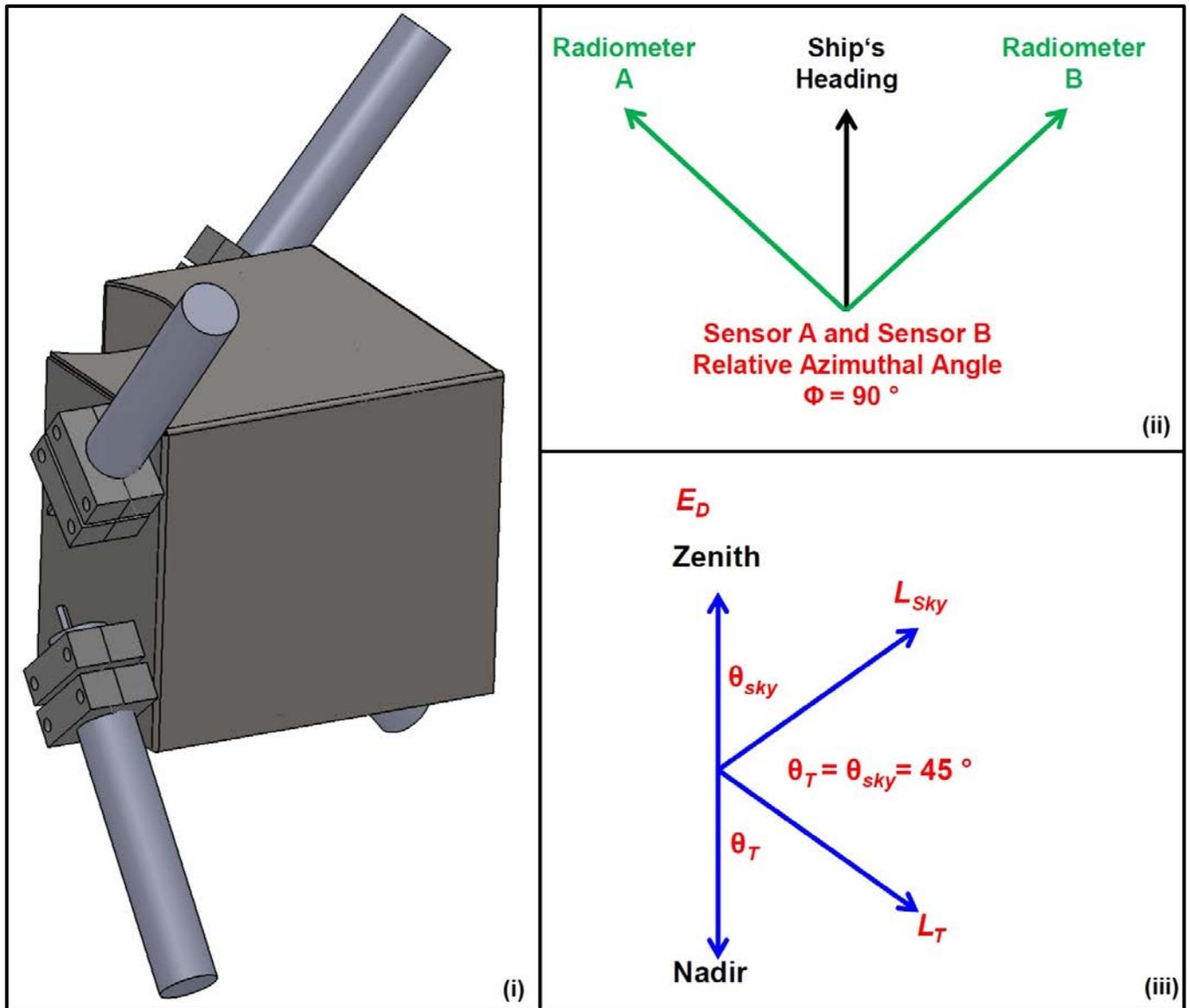
Wavelength h [nm]	R_{RS} [$\times 10^{-3}$ sr $^{-1}$]	Min R_{RS} [$\times 10^{-3}$ sr $^{-1}$]	Max R_{RS} [$\times 10^{-3}$ sr $^{-1}$]	UPD [%]	Max Error [$\times 10^{-4}$ sr $^{-1}$]
410	5.139	4.942	5.318	7.33	1.88
440	7.299	7.048	7.443	5.44	1.97
490	11.016	10.705	11.195	4.47	2.45
510	11.269	10.942	11.458	4.61	2.58
555	11.019	10.663	11.224	5.13	2.80
645	3.214	2.825	3.439	19.60	3.07



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444 Fig. 1. The camera system highlighted in yellow onboard R/V Heincke.

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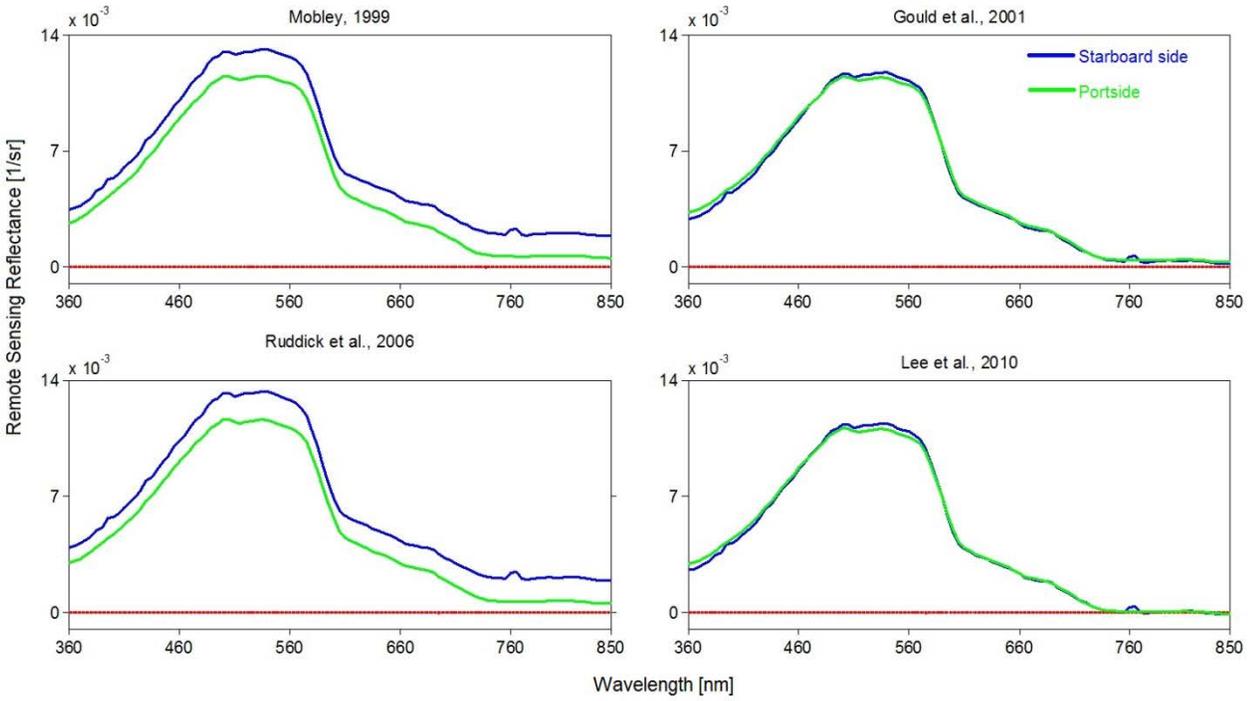
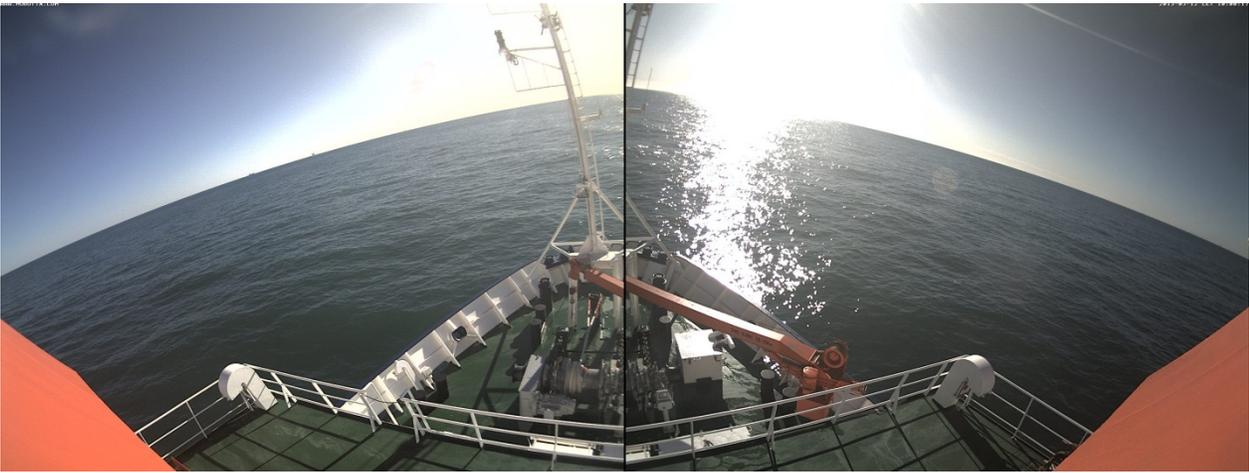
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Fig. 2. A schematic of the radiometer setup onboard the R/V Heincke. (i) is the model of the radiometers and the platform, (ii) a top view of the radiometers, and (iii) a side view of the radiometer geometry.

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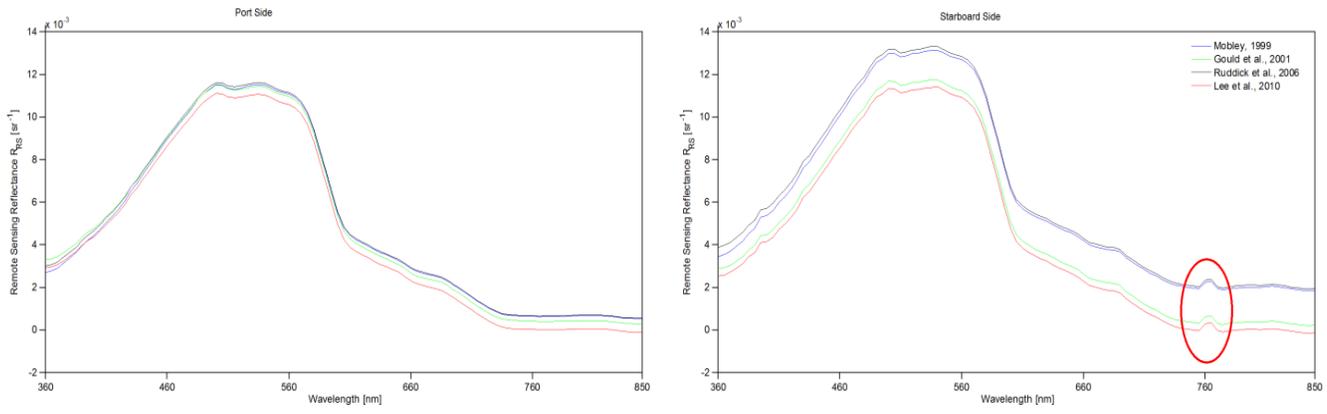


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453 Fig. 3. An example of sea surface and sky images collected onboard R/V Heincke with the matching
454 surface reflected glint corrected R_{RS} spectra on 12 March 2013 at 10:00. Red line indicates the zero
455 reflectance line.

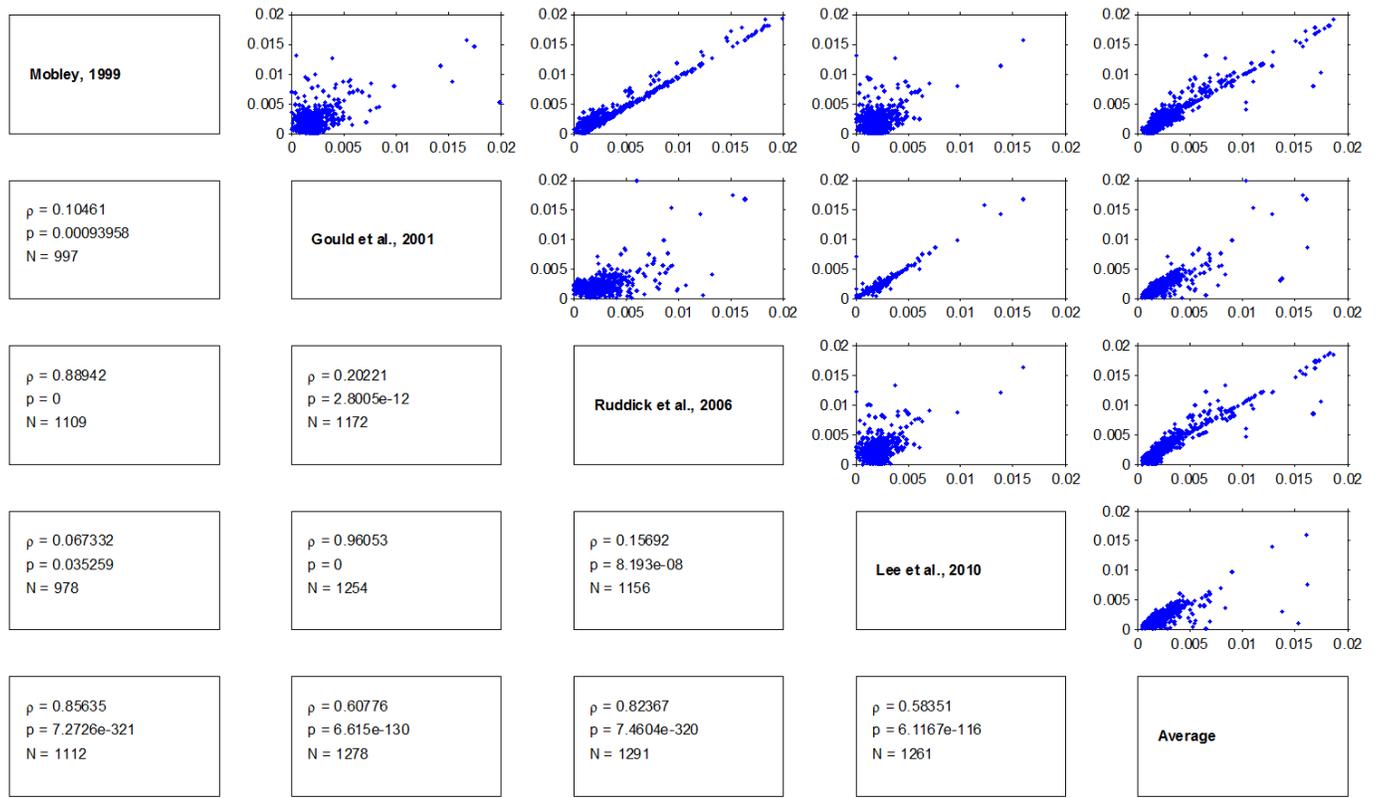
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458 Fig. 4. Example of a surface reflected glint correct Remote sensing reflectance (R_{RS}) spectra on 12
 459 March 2013 at 10:00 aboard R/V Heincke. The highlighted red part indicates a peak around 760 nm
 460 observed in spectra strongly influenced by surface reflected glint.

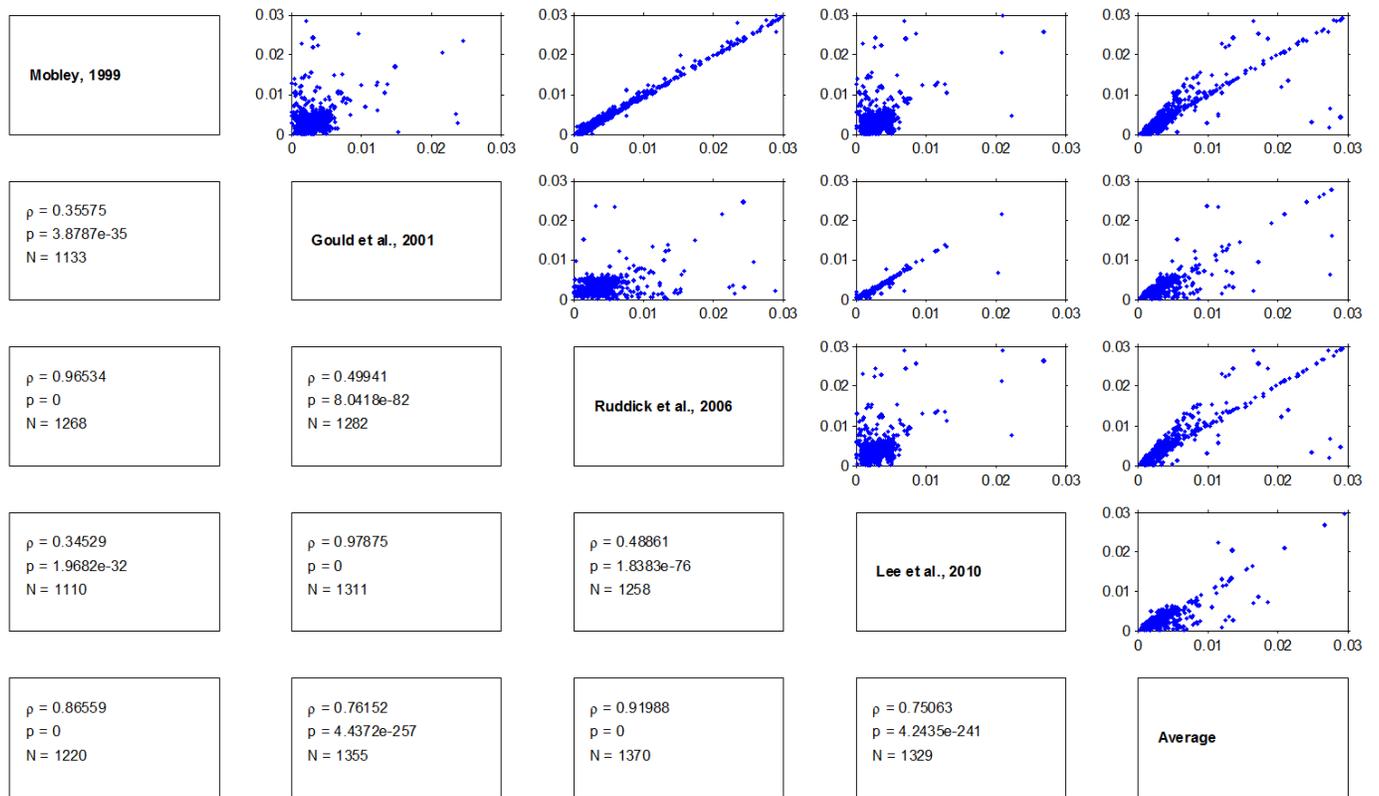
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463 Fig. 5. Spearman's rank-order correlation statistics at 440 nm for measurements from high latitude melt
 464 waters and fjordal waters as well as northwestern European shelf seas.

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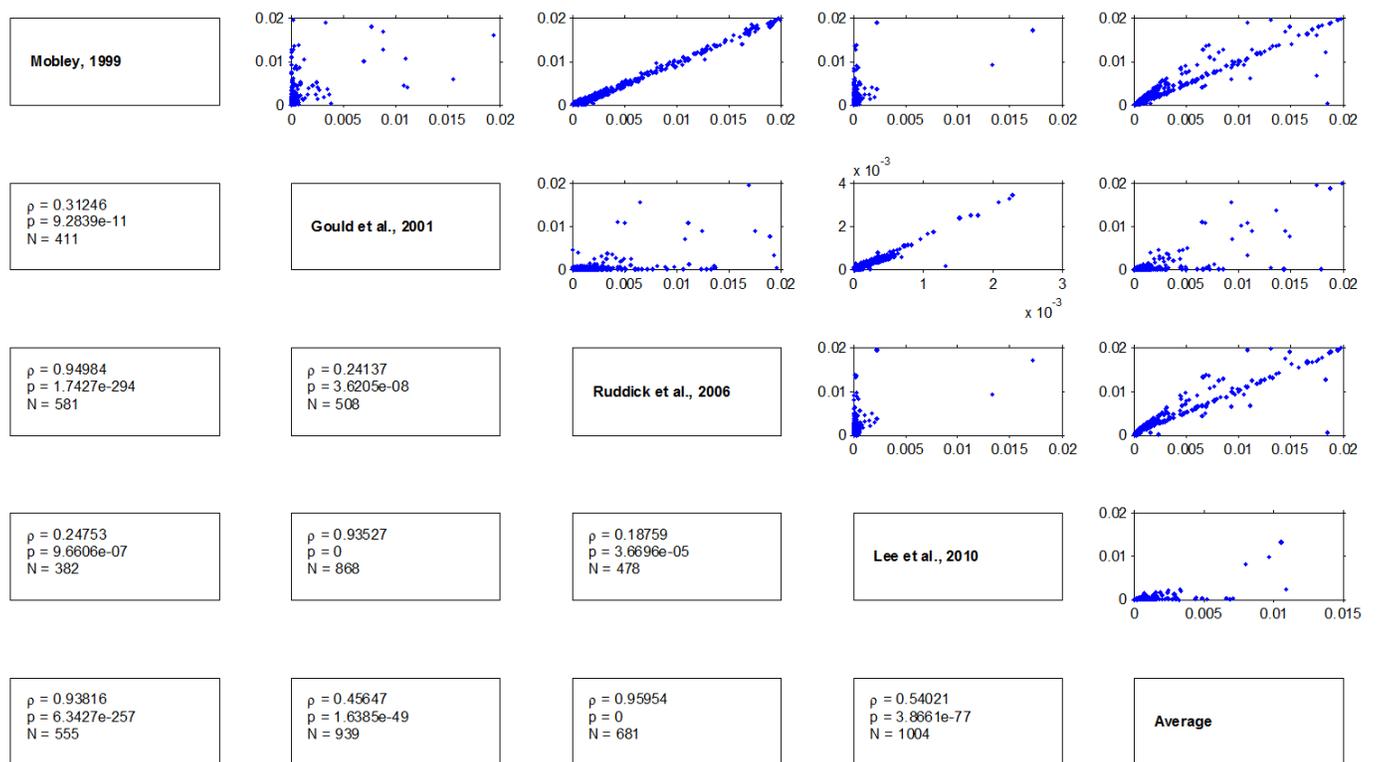
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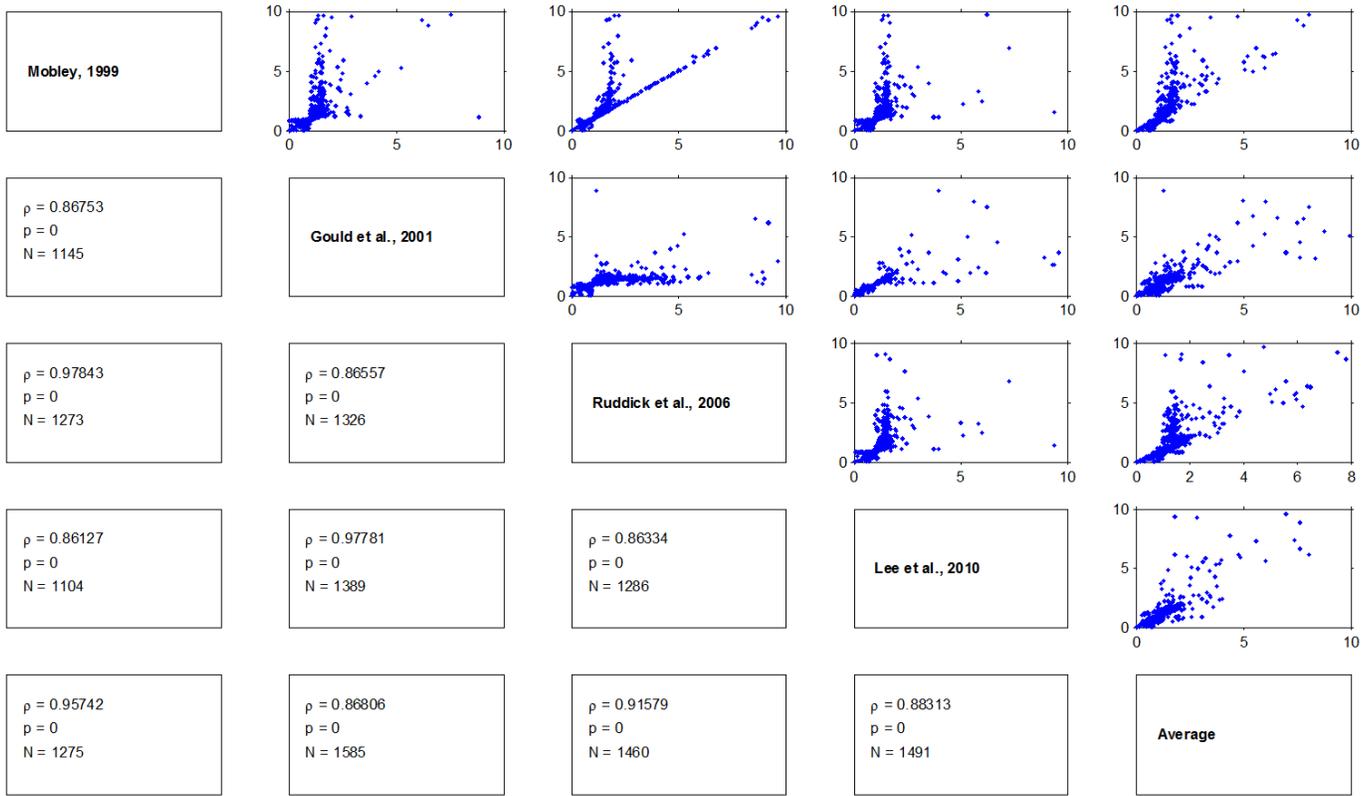
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Fig. 6. Spearman's rank-order correlation statistics at 555 nm measurements from high latitude melt waters and fjordal waters as well as northwestern European shelf seas.

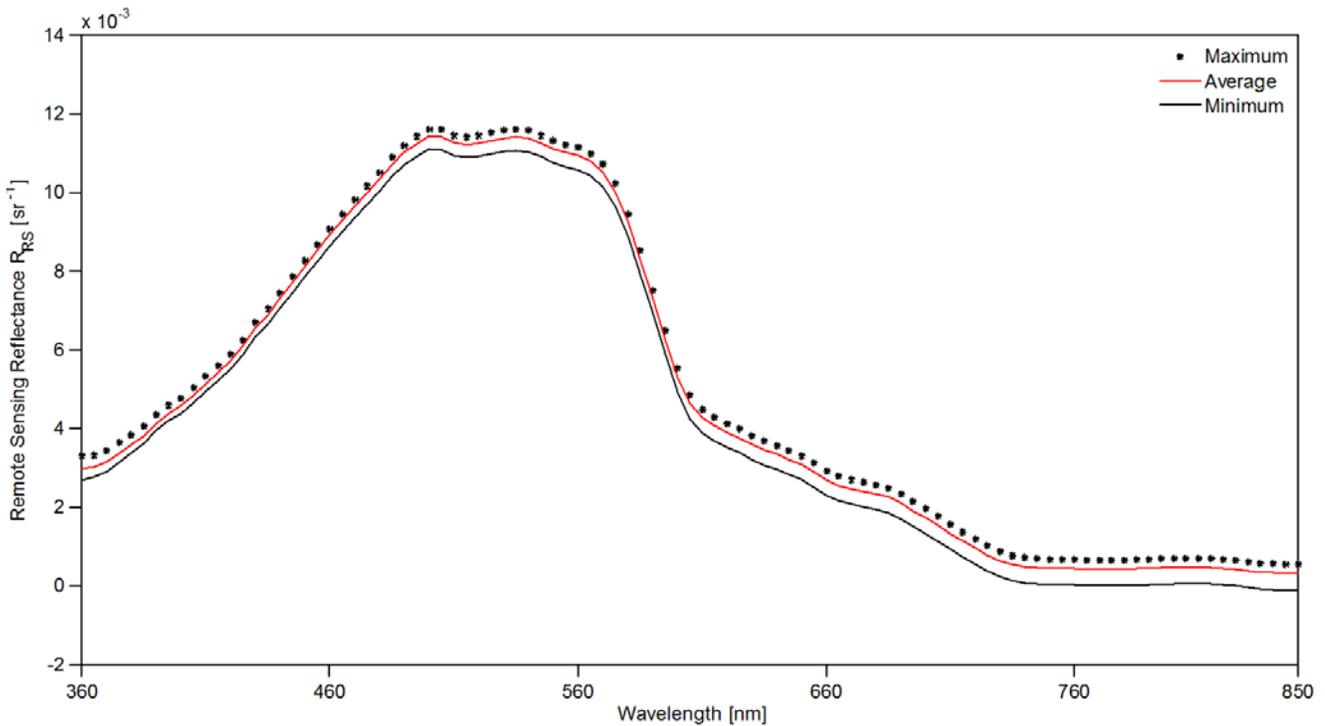


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471 Fig. 7. Spearman's rank-order correlation statistics at 715 nm measurements from high latitude melt
 472 waters and fjordal waters as well as northwestern European shelf seas.
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474
 475 Fig. 8. Spearman's rank-order correlation statistics at (490/555) nm measurements from high latitude
 476 melt waters and fjordal waters as well as northwestern European shelf seas.



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479 Fig. 9. Example of a surface reflected glint correct R_{RS} spectra on 12 March 2013 at 10:00 from the port
480 side aboard R/V Heincke.

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