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1 **Coastal and inland water pixels extraction algorithm (WiPE) from spectral shape**
2 **analysis and HSV transformation applied to Landsat 8 OLI and Sentinel-2 MSI**

3

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16

17 **Abstract:** Identification of water pixels over natural water bodies is a prerequisite step prior to applying
18 algorithms dedicated to the estimation of bio-optical properties of surface waters from remote sensing
19 observations. For visible remote sensing sensors, clouds affect the quantity and quality of the
20 observations, directly by hiding part of the scene and indirectly by their shadows. A certain level of
21 confusion could occur for detection of clouds over turbid (i.e. bright) waters and for detection of their
22 shadows over any kind of surface water. Some algorithms exist but their performance is not satisfactory,
23 especially over turbid waters where cloud-free pixels are sometimes classified as cloud or land, leading
24 to a loss of data. This is particularly important for medium spatial resolution observations such as those
25 performed by the Operational Land Imager (OLI) sensor on Landsat-8 or the Multispectral Instrument
26 (MSI) on Sentinel-2 (a and b). In the frame of this study, we developed a two-step algorithm for the

27 extraction of water pixels (referred to as WiPE) for these medium spatial resolution sensors. In contrast
28 to other approaches based on the top of atmosphere (TOA) reflectance, this algorithm uses the Rayleigh-
29 corrected TOA reflectance ($\rho_{rc}(\lambda)$) as input parameter allowing the spectral signature of each object to
30 be better characterized. The first step, based on the $\rho_{rc}(\lambda)$ spectral shape analysis of each object, allows
31 water pixels to be discriminated from cloud, vegetation, barren land, and constructions pixels. The second
32 step, in which the $\rho_{rc}(\lambda)$ spectra are transferred into the Hue-Saturation-Value space, greatly improves
33 the detection of cloud shadow over waters. This second step, based on the processing of the whole image,
34 does not require any knowledge on the location and altitude of clouds. Thin clouds are identified during
35 the two steps of the algorithm. This algorithm has been successfully tested over a broad range of
36 environments. WiPE, specifically designed for the extraction of water pixels, generally shows better
37 performance over turbid waters than the standard algorithm developed for Landsat imagery (Fmask).
38 This is explained by the fact that Fmask does not specifically focus on the detection of water pixels, but
39 on the masking of cloud, cloud shadow, and snow over land and water.

40

41 **Key word:** Medium Spatial Resolution Sensors, coastal and inland waters, water pixel extraction, cloud
42 mask.

43 **1. Introduction**

44 Landsat-8, launched on February 11st 2013, carries the Operational Land Imager (OLI) and the
45 Thermal InfraRed Sensor (TIRS). L8-OLI (Table 1) has four spectral bands in the visible, four in the
46 near infrared, and one panchromatic band, while TIRS collects signal within two thermal infrared bands.
47 Recent studies have demonstrated the potential of L8-OLI for ocean color related applications where its
48 medium-spatial resolution (30 m) provides new insights for a better understanding of processes occurring
49 in coastal waters (Pahlevan and Schott, 2013; Vanhellemont and Ruddick, 2014). Atmospheric correction
50 algorithms have been developed to retrieve the remote sensing reflectance ($R_{rs}(\lambda)$), where λ is the

51 wavelength in nm), from the top of atmosphere (TOA) radiometric signal measured by OLI (Franz et al.,
52 2015; Pahlevan et al., 2017).

53

54 Table 1. S2-MSI and L8-OLI spectral bands and spatial resolutions

55

Sentinel-2			Landsat-8		
Band	Wavelength (nm)	Spatial Resolution (m)	Band	Wavelength (nm)	Spatial Resolution (m)
1	421 - 457	60	1	433 - 453	30
2	439 - 535	10	2	450 - 515	30
3	537 - 582	10	3	525 - 600	30
4	646 - 685	10	4	630 - 680	30
5	694 - 714	20			
6	731 - 749	20			
7	768 - 796	20			
8	767 - 908	10			
8A	848 - 881	20	5	845 - 885	30
9	931 - 958	60			
10	1338 - 1414	60	9	1360 - 1390	30
11	1539 - 1681	20	6	1560 - 1660	30
12	2072 - 2312	20	7	2100 - 2300	30

56

57

58

59 Due to the increased radiometric sensitivity from 8-bit to 16-bit data in comparison with the
60 previous Landsat sensors series, the assessment of in water parameters, such as the suspended particulate
61 matter concentration (SPM), the Secchi-disk depth, and the colored dissolved organic matter (CDOM),
62 from $R_{rs}(\lambda)$ is now possible, mainly from empirical and regional approaches, with a relatively good
63 accuracy over coastal waters (Vanhellemont and Ruddick, 2014; Concha and Schott, 2016; Kutser et al.,
64 2016; Lymburner et al., 2016; Lee et al., 2016; Urbanski et al., 2016; Slonecker et al., 2016; Li et al.,
65 2017). A challenge, however, still remains to automatically detect water pixels over which these different

66 atmospheric and bio-optical algorithms can finally be applied. Cloud and cloud shadow should indeed
67 be correctly detected, which is still rather challenging over coastal and inland waters, bodies that are
68 generally turbid. An over-masking procedure results in a loss of water-pixels, while an under-masking
69 procedure results in a wrong assessment of the remote sensing reflectances and their associated in-water
70 components.

71 Numerous algorithms have been developed to detect and extract surface water from remote
72 sensing technology for about four decades. For example, the Normalized Difference Vegetation Index
73 (NDVI) (Rouse et al., 1973), based on the red and near-infrared bands, has been used to distinguish land
74 cover from clear to slightly turbid water surface (Vermote & Saleous, 2007 ; Jawak et al., 2015). To
75 specifically identify water pixels, the Normalized Difference Water Index (NDWI), based on the
76 difference between reflectance in the green band, which is greatly impacted by water surface, and the
77 one in the NIR band, has been introduced by McFeeters (1996). However, this very widely used index,
78 cannot efficiently suppress the signal from built-up land and water. Combination of this index with a
79 Geographic Information System (McFeeters, 2013), or modification of this index (MNDWI) by
80 substituting the medium infrared band for the near infrared band (Xue, 2006) have therefore been
81 proposed to improve the detection of water surface in environments with complex signal background.
82 The application of all the latter approaches require manually defined threshold values depending on the
83 study area, which may not be adequate for automatically detecting of water surface pixels whatever the
84 considered environment. Because of its relatively good performance, as well as its full automation, the
85 Fmask (Function of mask) algorithm is commonly used for masking cloud, cloud shadow, and snow in
86 Landsat images (Zhu and Woodcock, 2012). This algorithm is based on predefined thresholds of TOA
87 reflectance values at specific bands, cloud probability calculation, brightness temperature (BT) analysis,
88 NDVI, and normalized difference snow index (NDSI), for many different objects (land, water, cloud
89 shadow, snow, and cloud). Despite the recent improvements of Fmask (Zhu et al., 2015), which take
90 advantage of the new cirrus band for Landsat 8, and which use a dynamic threshold instead of a fixed

91 one for cloud detection over water, some wrong identifications of water pixels, as those presented in the
92 present study, still remain, especially over turbid waters (see section 4). This is explained by the fact that
93 Fmask does not specifically focus on the detection of water pixels, but on the masking of cloud, cloud
94 shadow, and snow over land and water. In contrast to Fmask, the present study specifically aims at
95 detecting water pixels of inland and coastal waters, and does not specifically focus on the individual
96 identification of each considered object. Because of the high contribution of the Rayleigh component to
97 the TOA signal, its contribution should first be removed for a better characterization of the spectral shape
98 of the reflectance over each object (Nordkvist et al., 2009). For these reasons, the present algorithm,
99 referred to as WiPE in the text (for Water Pixel Extraction), uses the Rayleigh- corrected top of
100 atmosphere reflectance spectra ($\rho_{rc}(\lambda)$) as input parameters. WiPE is based on the combination of spectral
101 criteria applied to $\rho_{rc}(\lambda)$ to mainly discriminate water pixels from land, clouds and vegetation pixels, and
102 on the application of a Hue-Saturation-Value or Brightness, HSV, analysis to optimize the detection of
103 thin clouds and cloud shadow pixels over water areas.

104 The database of L8-OLI and S2-MSI images collected over contrasted coastal and inland water
105 areas, and dedicated to the development and validation of the algorithm, is first presented. The new
106 algorithm is then described for L8-OLI. Finally, WiPE is evaluated from an independent validation
107 database, and the results are compared with those obtained by Fmask. While the present algorithm is
108 fully described for the OLI sensor, the same methodology is applied to MSI on Sentinel-2a (launched on
109 23 June 2015) which present some slight differences in terms of spectral bands and spatial resolutions
110 (Table 1). The adaptation of WiPE on S2-MSI is discussed at the end of the paper from illustration
111 examples. This adaptation, performed for S2a-MSI, can fully be applied on S2b-MSI, as the spectral
112 bands of S2a-MSI and S2b-MSI only differ by about less than one nanometer in the visible and NIR
113 spectral domains.

114 **2. Development and validation data sets**

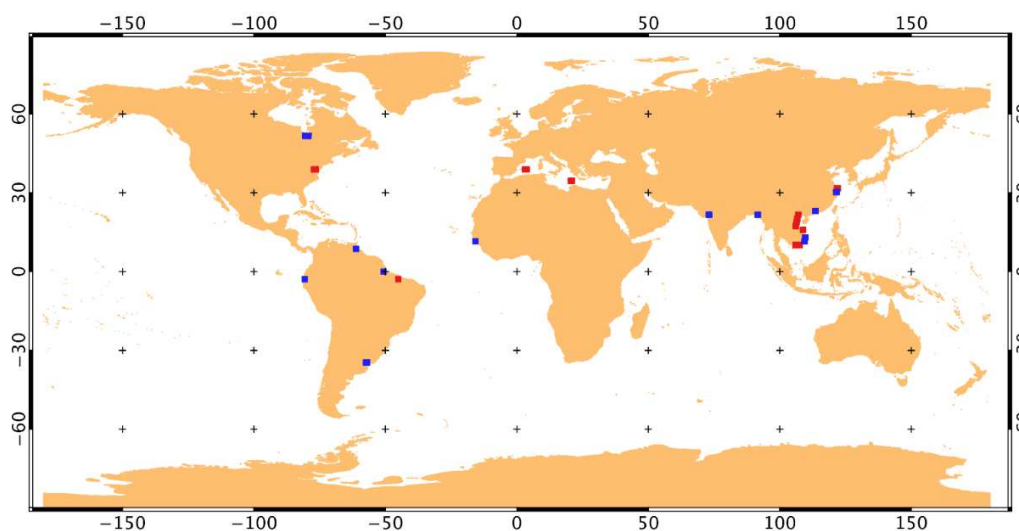
115 2.1 General description of the satellite data sets

116 Level-1 of Landsat-8 TOA reflectance and Brightness Temperature (BT) have been downloaded
117 from USGS (<https://landsat.usgs.gov/>) over different geographical locations covering contrasted
118 atmospheric and environmental conditions (Fig. 1). The whole dataset has been split into two different
119 sub-groups. The first group, gathers 196,738 independent pixels (with 164,681 water pixels) extracted
120 from 32 different scenes, is used for algorithm development. The second one is composed by 12 different
121 scenes for independent testing and validation of the algorithm. The mean and standard deviation values
122 of the sun zenith angle for the development and validation data sets are $28.3^{\circ} \pm 9.2^{\circ}$ and $34.4^{\circ} \pm 10.1^{\circ}$,
123 respectively. The percentage of cloud cover in the images used for the development and validation data
124 sets are $0.92 \pm 14.7\%$ and $24.6 \pm 16.6\%$, respectively. The cloud cover is much higher for the validation
125 data set to be able to test the algorithms over a variety of cloud types.

126 The top of atmosphere ($\rho_{\text{TOA}}(\lambda)$), as well as the Rayleigh-corrected ($\rho_{\text{rc}}(\lambda)$) reflectances are
127 provided over each considered object, which are water, cloud, thin cloud, cloud shadow, construction,
128 barren land, and vegetation. BT, one of the input parameters in Fmask, is also provided over each pixel
129 of each validation scene for the inter-comparison exercise. This dataset covers various bio-optical aquatic
130 environments such as river outlets characterized by brown waters characterized by high (Mekong river
131 delta, Amazon estuary, Rio de la Plata estuary, Gulf of Khambhat) to moderate (south of Hudson bay)
132 suspended sediment loads, green coastal waters with a high concentration of phytoplankton (aquaculture
133 areas in Chinese coastal waters, Halong bay, phytoplankton blooms in Vietnam coastal waters, and in
134 the Liguria sea), and blue offshore waters of the Mediterranean Sea. Water pixels for the development
135 data set have only been selected in coastal and offshore waters to limit mixed water/land situations
136 typically found in inland waters. These different locations have been chosen in order to cover a wide
137 range of water types based on our current knowledge of these specific areas, and on a visual examination
138 of Rayleigh corrected images. This broad range of aquatic environments is reflected in the large

139 variability of the Rayleigh-corrected reflectance spectra, $\rho_{rc}(\lambda)$, extracted over water pixels (Fig. 2). The
140 amplitude and spectral position of the maximum of $\rho_{rc}(\lambda)$, mainly driven by the bio-optical properties of
141 the water body span over a large range of values. For instance, the maximum of $\rho_{rc}(\lambda)$ is observed at
142 band 1, 2, 3, 4, and 5 for 2.3%, 22.9%, 45.4%, 26.6%, and 2.8% of the water pixels used in the
143 development data set (Fig. 2), respectively. This spectral shift reflects a change in the turbidity level, as
144 the maximum of water remote sensing reflectance is observed in the blue and near-infrared for clear and
145 very turbid waters, respectively (Han et al., 2016).

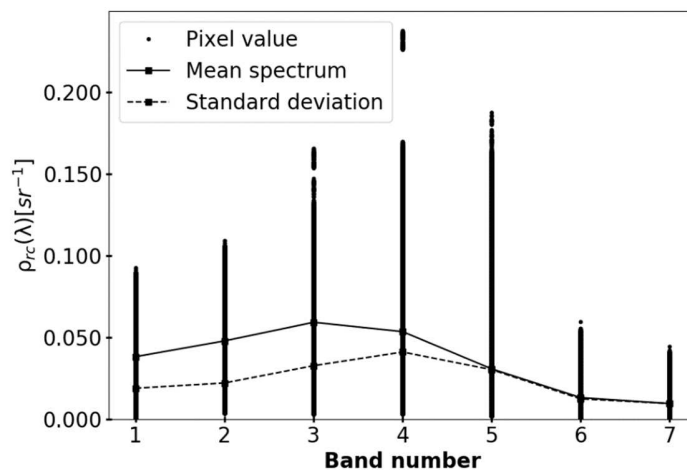
146



147

148 **Fig. 1.** Location of L8-OLI images used for the development (red dots, 32 different scenes) and validation
149 (blue dots, 12 different scenes) steps of the algorithm.

150



151

152 **Fig. 2.** Mean and standard deviation of $\rho_{rc}(\lambda)$ spectra over the 164,681 selected water pixels of the
 153 developing data set for L8-OLI.

154

155 In contrast to L8-OLI where each visible and NIR spectral channels used in WiPE have the same
 156 spatial resolution (i.e. 30 m), the MSI-S2 relevant channels present some discrepancies in terms of spatial
 157 resolution (Table 1). Following the two steps approach developed for L8-OLI, WiPE is adapted to S2-
 158 MSI based on a development data set of 65 S2-MSI images collected from
 159 <https://scihub.copernicus.eu/dhus> in contrasted aquatic environments (European, South America,
 160 Vietnam, and China coastal waters). Considering the similar performance of WiPE on S2-MSI and L8-
 161 OLI images (not shown here), and because the validation of WiPE is deeply examined for OLI in the
 162 present paper, we will only discuss the performance of WiPE for S2-MSI observations on two
 163 representative examples, the Huangmao river estuary (China) and the Tonle Sap lake (Cambodia). We
 164 will specifically focus on the impact of the MSI per-channel spatial resolution variation.

165

166 *2.2. The Rayleigh correction procedure*

167 In order to better characterize the spectral signature of the different selected objects, the signal
 168 due to air molecules, which contributes to a large part of $\rho_{TOA}(\lambda)$, should be removed. The TOA
 169 reflectance, $\rho_{TOA}(\lambda)$, can be developed as follows (Gordon, 1997):

$$170 \quad \rho_{TOA}(\lambda) = \rho_R(\lambda) + \rho_a(\lambda) + \rho_{Ra}(\lambda) + T(\lambda)\rho_g(\lambda) + t(\lambda)\rho_{wc}(\lambda) + t(\lambda)\rho_w(\lambda) \quad (1)$$

171 where $\rho_R(\lambda)$ is the reflectance due to multiple scattering of a purely air molecules atmosphere, $\rho_a(\lambda)$ is
 172 the reflectance of multiple scattering by aerosols in a pure aerosol atmosphere, and $\rho_{Ra}(\lambda)$ stands for the
 173 interaction term in a real atmosphere containing both molecules and aerosols. $T(\lambda)$ and $t(\lambda)$ are the direct
 174 and diffuse transmittances of the atmosphere, respectively. $\rho_g(\lambda)$, $\rho_{wc}(\lambda)$, and $\rho_w(\lambda)$ are the reflectances
 175 due to sun glint, whitecaps, and in-water optically significant components, respectively. The sunglint
 176 and whitecaps reflectances are related to wind speed and geometry (Wang and Bailey, 2001).

177 The pixel value recorded by L8-OLI at the top of the atmosphere is a digital number, from which
 178 the TOA radiance, $L_{TOA}(\lambda)$, and reflectance, $\rho_{TOA}(\lambda)$, are calculated through Eq.(2) and Eq.(3),
 179 respectively (Vanhellemont and Ruddick, 2014).

$$180 \quad L_{TOA}(\lambda) = M_L(\lambda)Q_{cal}(\lambda) + A_L(\lambda) \quad (2)$$

$$181 \quad \rho_{TOA}(\lambda) = \frac{\pi L_{TOA}(\lambda)d^2}{F_0(\lambda)\cos(\theta_0)} \quad (3)$$

182 where $L_{TOA}(\lambda)$ is the spectral radiance (in $\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$), $M_L(\lambda)$ the radiance multiplicative scaling
 183 factor (i.e. gain) for each band, $Q_{cal}(\lambda)$ the Level-1 pixel value in digital number, and $A_L(\lambda)$ is the radiance
 184 additive scaling factor (i. e. offset) for each band. d , F_0 , and θ_0 are the Earth-Sun distance in Astronomical
 185 Units, the band average solar irradiance, and the sun zenith angle, respectively.

186 The reflectance due to Rayleigh scattering in a purely molecular atmosphere, $\rho_R(\lambda)$, is given by the
 187 following equation (Gordon et al., 1988; Wang and King, 1997):

188
$$\rho_R(\lambda) = \tau_R(\lambda)p_R(\theta)(4\cos\theta_0\cos\theta_v)^{-1} \quad (4)$$

189 where $\tau_R(\lambda)$ is the Rayleigh scattering optical thickness, $p_R(\theta)$ the Rayleigh scattering phase function at
 190 a scattering angle, θ , θ_v the viewing zenith angle, and θ_0 the sun viewing angle. The optical thickness at
 191 the atmospheric pressure P is calculated as follows:

192
$$\tau_R(\lambda) = \frac{P}{P_0}\tau_{R0}(\lambda) \quad (5)$$

193 where $\tau_{R0}(\lambda)$ is the optical thickness at the standard atmospheric pressure P_0 of 1013.25 mbar.

194 The Rayleigh scattering phase function $p_R(\theta)$ is defined as:

195
$$p_R(\theta) = P_R(\theta_-) + [r(\theta_v) + r(\theta_0)]P_R(\theta_+) \quad (6)$$

196 The term involving θ_- provides the contribution due to photons which are backscattered from the
 197 atmosphere without interacting with the sea surface. The term involving θ_+ accounts for photons which
 198 are scattered in the atmosphere toward to the sea surface. These terms are computed from sun-sensor
 199 geometry as:

200
$$\cos(\theta_{\pm}) = \pm\cos(\theta_0)\cos(\theta_v) - \sin(\theta_0)\sin(\theta_v)\cos|\phi_0 - \phi_v| \quad (7)$$

201 with ϕ_0 and ϕ_v are sun and sensor azimuth angles. $r(\theta)$ is the Fresnel reflectance for air-incident rays at
 202 incidence angle θ . The Rayleigh scattering phase function $P_R(\theta)$ for scattering angle θ , and the Fresnel
 203 reflectance $r(\theta)$ for air-incident rays at an incidence angle θ are calculated as follows:

204
$$P_R(\theta) = \frac{3}{4}(1 + \cos^2(\theta)) \quad (8)$$

205
$$r(\theta) = 0.5 \left\{ \frac{\sin^2(\theta - \theta_t)}{\sin^2(\theta + \theta_t)} + \frac{\tan^2(\theta - \theta_t)}{\tan^2(\theta + \theta_t)} \right\} \quad (9)$$

206
$$\theta_t = \sin^{-1}(n_w \sin(\theta)) \quad (10)$$

207 The Rayleigh-corrected reflectance is defined in Eq.(11) as:

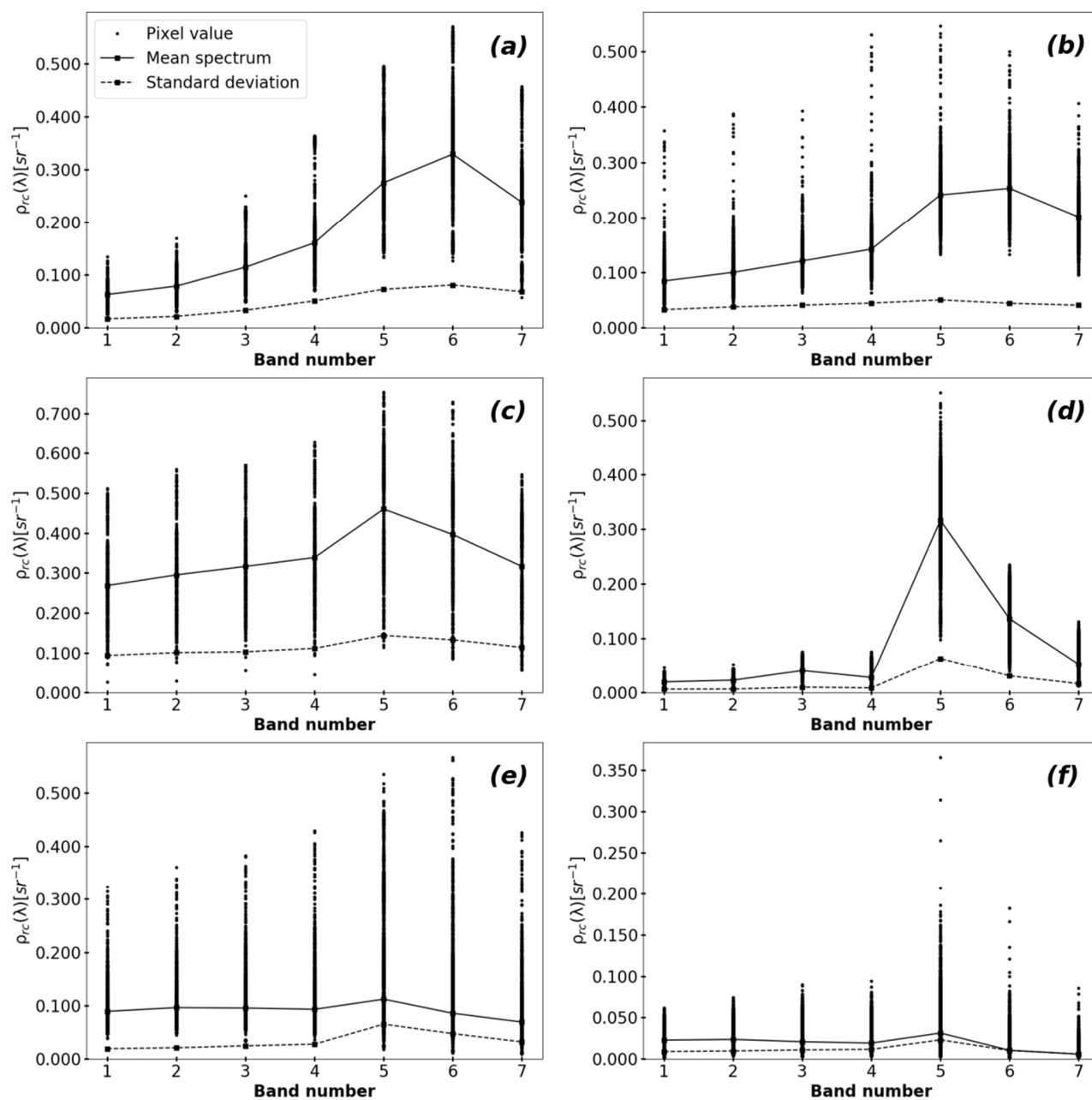
$$208 \quad \rho_{rc}(\lambda) = \rho_{TOA}(\lambda) - \rho_R(\lambda) = \rho_a(\lambda) + \rho_{Ra}(\lambda) + T(\lambda)\rho_g(\lambda) + t(\lambda)\rho_{wc}(\lambda) + t(\lambda)\rho_w(\lambda) \quad (11)$$

209 Rayleigh scattering generally contributes about 80% to 90% of the TOA reflectance in the blue part of
 210 the spectrum from clear to turbid waters, respectively (Gordon et al., 1988; IOCCG, 2010).

211 2. 3. Spectral database for each selected object

212 Classified objects are manually selected on Rayleigh-corrected color image composites.
 213 Polygons are drawn over homogenous areas of the considered objects, and pixels are counted using the
 214 QGIS software. Mixed situations are manually disregarded, except those specifically considered here as
 215 cloud shadows and thin clouds over land and water. All TOA reflectance and Rayleigh-corrected spectra
 216 are stored for each of the following objects: clouds over land and water (664 pixels), thin clouds over
 217 land and water (9493 pixels), shadows over land and water (13,582 pixels), water (164,681 pixels),
 218 vegetation (4817 pixels), barren land (2103 pixels), and constructions (1398 pixels). The whole database
 219 of the $\rho_{rc}(\lambda)$ spectra over the six non-water selected objects is provided in Fig. 3. Similarly to the water
 220 pixels (Fig. 2), each of the previous object is characterized by a large range of variability of $\rho_{rc}(\lambda)$ spectra,
 221 as shown by the large standard deviations observed around each mean spectrum. Based on this latter
 222 pattern, we can assume that the database covers a broad range of situations for each object, which makes
 223 it quite suitable for the algorithm development phase.

224



225

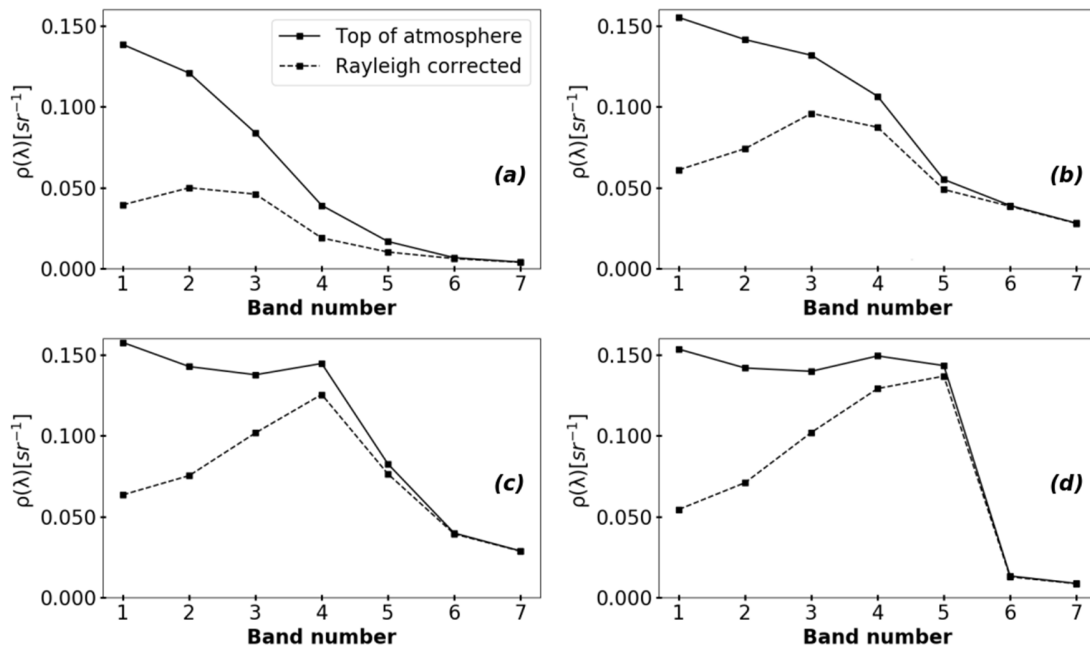
226 **Fig. 3.** Mean and standard deviation of $\rho_{rc}(\lambda)$ spectra collected by L8-OLI over (a) barren land, (b)

227 construction, (c) clouds over land and water, (d) vegetation, (e) thin clouds over land and water, and (f)

228 cloud shadows over land and water.

229

230 The benefit of using $\rho_{rc}(\lambda)$ instead of $\rho_{TOA}(\lambda)$ to detect water pixels is illustrated in Fig. 4, where
 231 typical spectra over water bodies are displayed. From clear (Fig. 4a) to very turbid waters (Fig. 4d) the
 232 spectral shape (as well as the amplitude) of $\rho_{rc}(\lambda)$ significantly differs from one water type to another.
 233 These latter spectral shape differences are less pronounced for $\rho_{TOA}(\lambda)$, especially between clear (Fig.
 234 4a) and green water (Fig. 4b).



235
 236 **Fig. 4.** Different $\rho_{rc}(\lambda)$ and $\rho_{TOA}(\lambda)$ spectra collected by L8-OLI over (a) blue (i.e. clear) (b) green, (c)
 237 turbid, and (d) very turbid water areas.

238

239 3. Development of the new algorithm (referred to as WiPE)

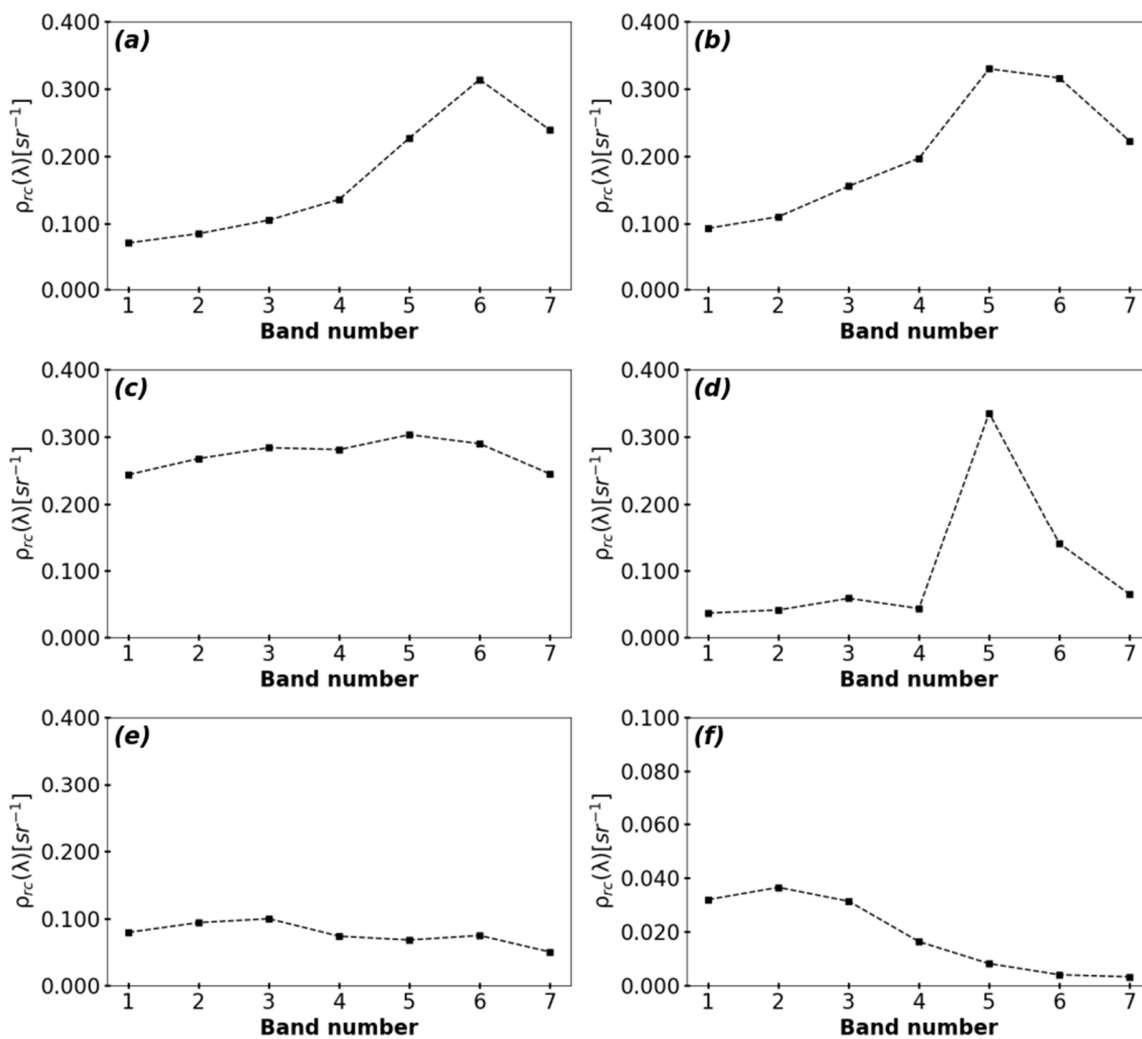
240 3.1. General approach

241 While the average $\rho_{rc}(\lambda)$ spectra for the different identified objects present significant differences
 242 in terms of spectral shape and amplitude, the associated large standard deviation values (Fig. 3) also
 243 stress a potential overlap between them. This patterns has oriented the development of the algorithm

244 through the use of a clustering approach developed in different spaces generated by the combination of
245 $\rho_{rc}(\lambda)$ (or $\rho_{rc}(\lambda)$ ratios) spectral values (first step of the algorithm), or by the combination of $\rho_{rc}(\lambda)$, V,
246 and S values of the HSV transformation (second step of the algorithm).

247 Typical examples of $\rho_{rc}(\lambda)$ spectra, which allow the understanding of the different spectral criteria
248 adopted in WiPE, are displayed over the six non-water objects in Fig. 5. With a relatively sharp increase
249 of $\rho_{rc}(\lambda)$ from band 1 (blue) to band 5 (near infrared), the barren land (Fig. 5a) and construction spectra
250 (Fig. 5b) significantly differ from other objects. This spectral shape, combined with the high peaks in
251 bands 5 (near infrared) and 6 (short wave infrared), allow barren land (Fig. 5a), and construction (Fig.
252 5b) to be distinguished from the other objects. In the same way, the sharp increase of $\rho_{rc}(\lambda)$ observed
253 between bands 4 and 5 for vegetation pixels (Fig. 5d) is a remarkable identification pattern of the
254 corresponding pixels. Further, the relatively flat $\rho_{rc}(\lambda)$ spectral shape, associated with a high level of
255 signal in the blue-red part of the spectrum, allow clouds to be relatively well identified from other objects
256 (Fig. 5c). Based on these observations, criteria have been developed on the spectral shape and amplitude
257 of $\rho_{rc}(\lambda)$ spectra in order to distinguish water pixels from land (vegetation, barren land, and construction)
258 and clouds over water. The application of these different spectral criteria represents the first step of the
259 algorithm (Fig. 6). In contrast to the previous objects, the $\rho_{rc}(\lambda)$ spectra over thin cloud (Fig. 5e) and
260 shadow (Fig. 5f) pixels may strongly be modified by the spectra of the overlaid water pixels which makes
261 the identification of these two objects over water areas very challenging from spectral shape analysis as
262 performed in the first step of the algorithm. For that purpose, the second step of the algorithm is based
263 on a multispectral colorimetric method, i. e., HSV transformation, which allows a better identification of
264 water pixels in these difficult configurations (Fig. 6).

265



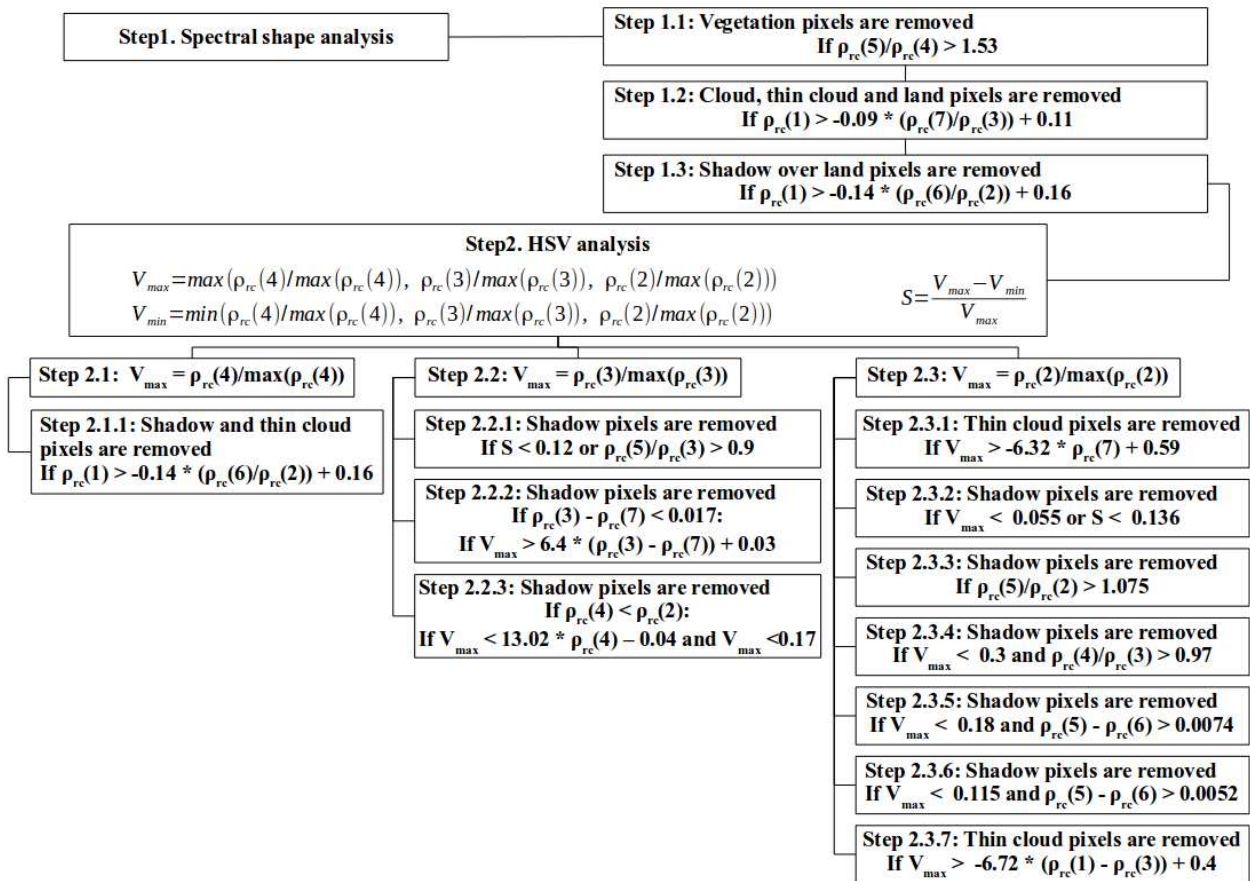
266

267 **Fig. 5.** Examples of $\rho_{rc}(\lambda)$ spectra collected by L8-OLI over the following non-water objects:(a) barren
 268 land, (b) construction, (c) clouds over water, (d) vegetation, (e) thin clouds over green water, and (f)
 269 clouds shadow over clear water.

270 3.2. First step of the algorithm: the spectral shape analysis

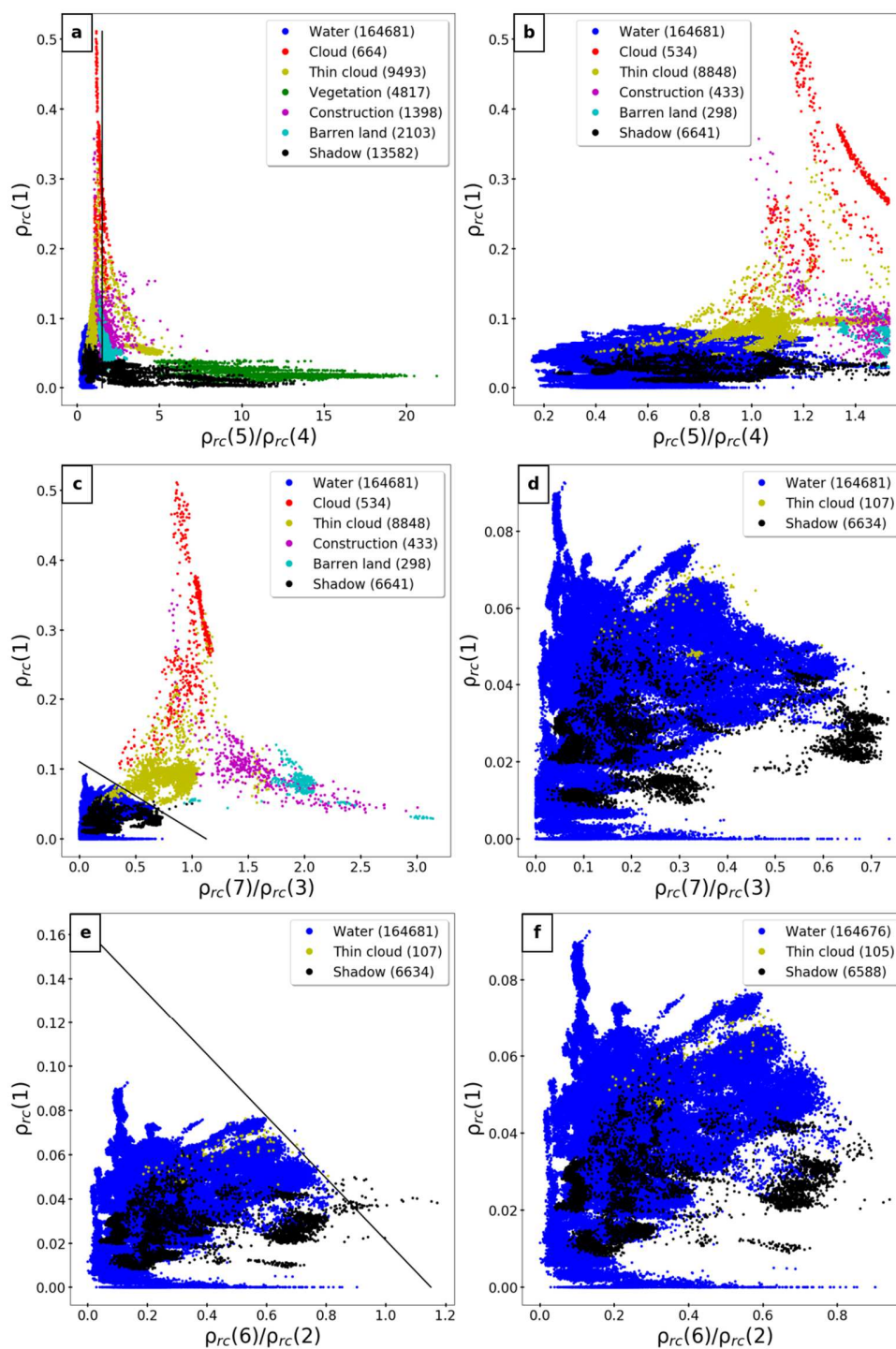
271 Spectral shapes and amplitude of $\rho_{rc}(\lambda)$ spectra over all objects are used for the algorithm
 272 development. Some objects with specific $\rho_{rc}(\lambda)$ spectral signature will be masked in the first step (Fig.
 273 6). This is the case of vegetation, barren land, construction, clouds, and shadow over land that will be
 274 removed based on some different combinations of $\rho_{rc}(\lambda)$ band ratios. Standard indexes, as those presented

275 in the introduction (e.g. NDWI; MNDWI), have also been tested but they did not provide any better
 276 results compared to those selected for step 1. The different equations and threshold values used in the
 277 two steps of the WiPE algorithm and presented in the flowchart (Fig. 6), have been empirically defined
 278 from visual examination of the data points in the different considered (x; y) spaces (Fig. 7).



279

280 **Fig. 6.** The logic flow of the water extraction pixel algorithm based on the combination of spectral shape
 281 analysis (step 1) and HSV analysis (step 2) for the L8-OLI sensor. This flowchart requires the Rayleigh
 282 corrected reflectance (Eq.11) at bands 1, 2, 3, 4, 5, 6, and 7 as input parameters.



283

284 **Fig. 7.** (left panels) Scatter plots of $\rho_{rc}(\lambda)$ as a function of $\rho_{rc}(\lambda)$ band ratios for the seven different objects
 285 of the development data set. The black line corresponds to the limit adopted to remove (a) vegetation
 286 (step 1.1), (c) clouds, construction, and barren land (step 1.2), and (e) cloud shadow over land pixels
 287 (step 1.3). Each color corresponds to a different object as indicated. The number of pixels before (panels

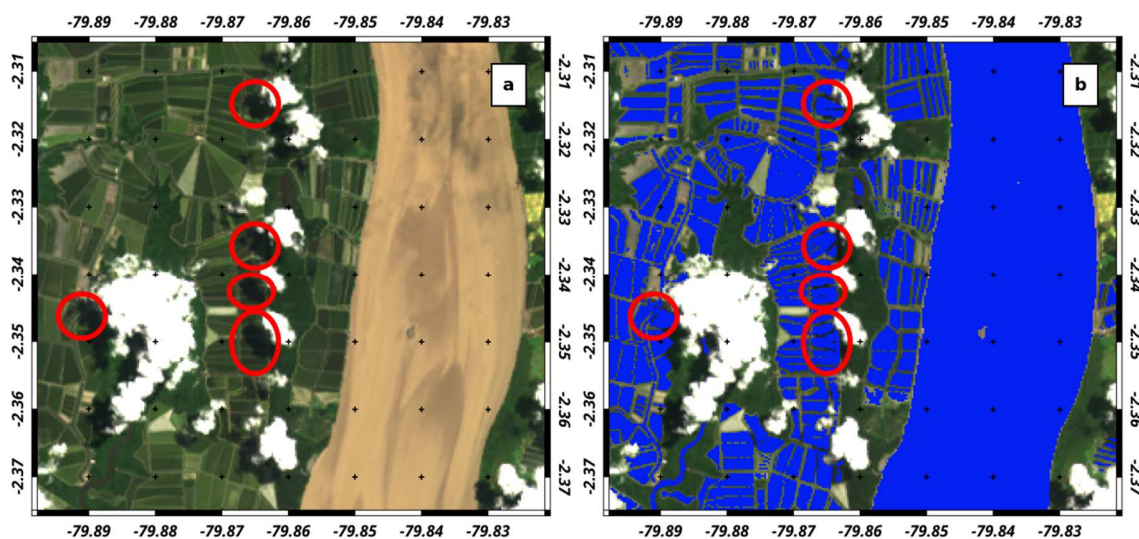
288 a, c, and e) and after (panels b, d, and f) the application of each criterion adopted in steps 1.1, 1.2, and
289 1.3 are provided in each panel.

290

291 Because of their very specific spectral signatures in the NIR domain (Figure 5d), vegetation pixels
292 are the first to be removed (step 1.1 in Fig. 6). Pixels with near infrared to red ratio value, $\rho_{rc}(5)/\rho_{rc}(4)$,
293 greater than 1.53 are identified as vegetation in the $(\rho_{rc}(5)/\rho_{rc}(4); \rho_{rc}(1))$ space (Fig. 7a). This threshold
294 value, manually fixed based on the examination of the data points in the $(\rho_{rc}(5)/\rho_{rc}(4); \rho_{rc}(1))$ space,
295 allows vegetation pixels to be remarkably well separated from water pixels (Fig. 7b), avoiding the mixing
296 of water and vegetation pixels even over very challenging situations such as inland productive waters. In
297 addition to removing the totality of the vegetation pixels, the application of this ratio also removed many
298 pixels from other objects, such as barren land (86%), thin clouds (7%) and almost all shadow pixels over
299 land (Fig. 7b). Clouds over land and water pixels present the highest Rayleigh-corrected reflectance in
300 almost every bands (Fig. 5c), but because of the high range of variability observed at each band, cloud
301 pixels may be difficult to distinguish from barren land (Fig. 5a) and construction (Fig. 5b) pixels which
302 present relatively similar spectral shape. For this reason, cloud over water and land, barren land, and
303 construction pixels are removed simultaneously at the step 1.2, using a combination of $\rho_{rc}(1)$ and
304 $\rho_{rc}(7)/\rho_{rc}(3)$ (see step 1.2 in Fig. 6). When $\rho_{rc}(1)$ is higher than $-0.09*\rho_{rc}(7)/\rho_{rc}(3) + 0.11$ the pixel is
305 rejected (Fig. 7c). By pulling cloud, barren land, and construction all together, this test will not allow for
306 a specific identification of these three different objects. However, that specific identification of non-water
307 objects is not the objective of the present method, which is only dedicated to the extraction of free water
308 pixels. Interestingly, this test also removed almost all thin clouds (Fig. 7d) over land and waters (98.9%).
309 The remaining thin-cloud pixels (1.1%) after the application of this first step are only found over water
310 pixels (Fig. 7d).

311 Shadow pixels are by essence difficult to remove, due to their relatively low reflectance value
312 and the strong impact of the spectral shape of the overlaid object. Based on the development database,
313 identified shadow pixels over land present a minimum $\rho_{rc}(2)$ value, while almost all land objects have
314 $\rho_{rc}(6) > \rho_{rc}(2)$. For that purpose the $\rho_{rc}(6)/\rho_{rc}(2)$ ratio, which presents a large range of variability, is
315 plotted against $\rho_{rc}(1)$, for which shadow pixels over land show the lowest variability compared to other
316 bands (Fig. 5f). Based on these observations, pixels with $\rho_{rc}(1)$ higher than $-0.14 * \rho_{rc}(6)/\rho_{rc}(2) + 0.16$ are
317 rejected (Fig.7e). The application of this criterion allows one to remove the remaining shadow pixels
318 over land that were still present after step 1.1. Only shadow pixels over water remain (the black dots in
319 Fig. 7f). Shadow pixels over water or land can be distinguished from one another, because, while the
320 $\rho_{rc}(\lambda)$ signal over these two different objects is undoubtedly attenuated by clouds shadow, the marked
321 differences in their spectral shapes are still noticeable, allowing the differentiation between shadow over
322 land and shadow over water. The performance of the spectral shape analysis procedure is illustrated over
323 a very complex aquaculture area at Rio Guayas in Ecuador where water and vegetation areas are
324 especially difficult to distinguish from one another on the Red-Green-Blue (RGB) composite (Fig. 8a).
325 Distinction between waters and vegetation/land/clouds pixels is very well performed. This has been
326 confirmed by a visual examination of images provided on google earth allowing a distinct identification
327 of aquaculture farms. However, while cloud shadows over land are appropriately masked, cloud shadows
328 areas over water (red circles in Fig. 8a) are misleadingly identified as water.

329



330

331 **Fig. 8.** (a) RGB image collected by L8-OLI over an aquaculture area at Rio Guayas in Ecuador
 332 (17/05/2015). (b) water pixel extraction (in blue) showing the performance of the spectral shape analysis
 333 (first step) to distinguish vegetation/cloud/land and water pixels in such challenging environment. At this
 334 stage (step 1), pixels with shadow over water are still not removed and are falsely identified as water (see
 335 red circles).

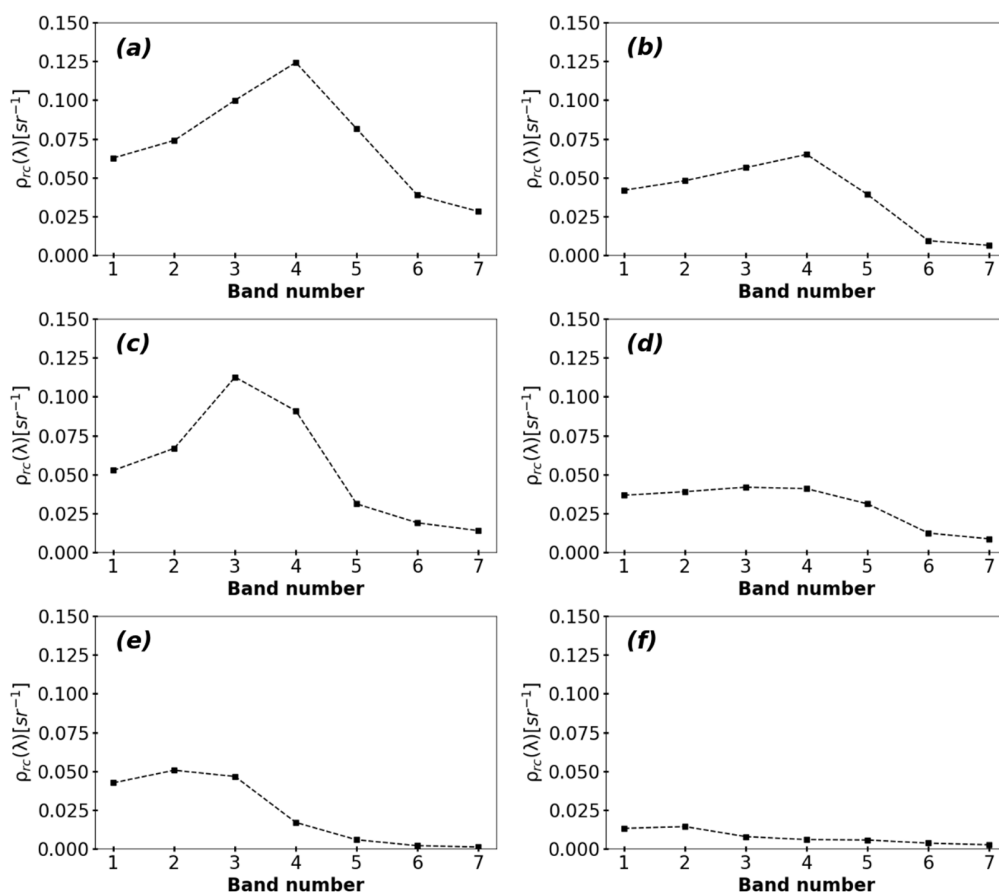
336

337 3.3. Second step of the algorithm: the HSV approach

338 Based on the spectral shape analysis developed in the first step of the algorithm, cloud over land
 339 and water, shadow over land, vegetation, barren land, and construction pixels are remarkably well
 340 removed. At this stage, only water pixels, thin clouds and shadow over water pixels remain. Cloud
 341 shadow pixels over water may therefore falsely be considered as water (Fig. 8). The significant
 342 differences observed in the $\rho_{rc}(\lambda)$ spectral shape over turbid (Fig. 9a), green (Fig. 9c), and clear (Fig. 9e)
 343 waters fade away in presence of shadow (Fig. 9b, d, and f). For this reason, Rayleigh-corrected
 344 reflectance spectra are transferred into the HSV color space which uses Hue, Saturation, and Value for
 345 color representation. In contrast to the standard RGB color space, where the color information and its
 346 intensity are generally mixed, the HSV color space is better adapted for image analysis and segmentation

347 (Smith, 1978; Ganesan et al., 2014). For instance, this color transformation, based on a mechanism of
 348 human model, has facilitated the extraction of water pixels over land (Pekel et al., 2014; Singh et al.,
 349 2016), and the correction of thin clouds which have high brightness, low saturation, and contrast (Pratt
 350 et al., 2001; Shen et al., 2015).

351



352

353 **Fig. 9.** Left panels - $\rho_{rc}(\lambda)$ spectra collected by L8-OLI over (a) turbid water, (c) green water, and (e)
 354 blue water. Right panels - $\rho_{rc}(\lambda)$ spectra for shadow pixels over (b) turbid water, (d) green water, and (f)
 355 blue water.

356

357 Hue is the angular component and indicates the color relative to the wavelength. The Hue
 358 component values, H, range between 0° to 360°, and represents the Hue of red (from 0° to 60°), yellow

359 (from 60° 120°), green (120° to 180°), etc. The Saturation component, S, is determined by the
 360 combination of light intensity and how much it is distributed across the spectrum. It describes how white
 361 the color is (a white object has a S value of 0). For instance, a pure green is fully saturated, with a
 362 saturation of 1 while tints of green have saturations less than 1. At last, the Value component, V, describes
 363 the intensity (or brightness) of the color of a considered pixel for a given image. In contrast to H, both S
 364 and V values are between 0 and 1. Because the Hue of the ground object is relatively invariant in presence
 365 of thin clouds (Shen et al., 2015), only the value, V, and saturation, S, will be taken into account in the
 366 present algorithm. The S and V values of the Rayleigh-corrected spectra are calculated as follows:

$$367 \quad S = \frac{(V_{max} - V_{min})}{V_{max}} \quad (12)$$

368 with V_{max} and V_{min} defined as:

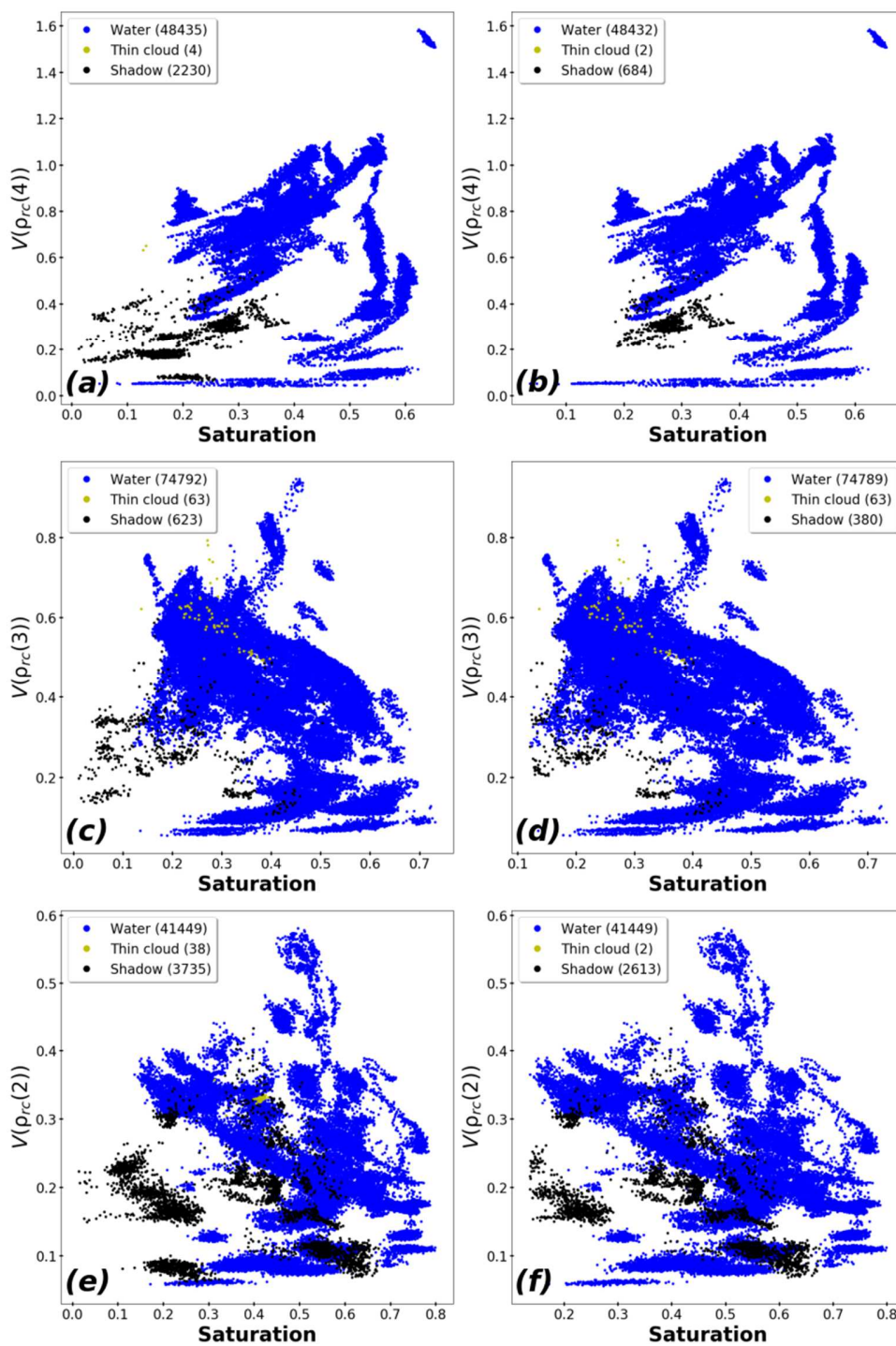
$$369 \quad V_{max} = \max \left(\frac{\rho_{rc}(4)}{\max(\rho_{rc}(4))}, \frac{\rho_{rc}(3)}{\max(\rho_{rc}(3))}, \frac{\rho_{rc}(2)}{\max(\rho_{rc}(2))} \right) \quad (13)$$

$$370 \quad V_{min} = \min \left(\frac{\rho_{rc}(4)}{\max(\rho_{rc}(4))}, \frac{\rho_{rc}(3)}{\max(\rho_{rc}(3))}, \frac{\rho_{rc}(2)}{\max(\rho_{rc}(2))} \right) \quad (14)$$

371 where $\max \rho_{rc}(i)$ represents the maximum value of $\rho_{rc}(i)$ observed over the whole image for
 372 the band i. Depending on the spectral band where V_{max} is obtained, different criteria involving V_{max} and
 373 S are applied to extract shadow as well as thin cloud pixels over water (Fig. 6). Importantly, in contrast
 374 with the first step which is a pixel per pixel approach, the maximum values are here assessed over the
 375 whole scene. Figure 10 shows the remaining pixels identified in Figure 7f and transferred into HSV space
 376 for the three possible values of V_{max} : when V_{max} is observed in the red (Fig. 10a,b), green (Fig. 10c, d),
 377 and blue (Fig. 10e, f). The sum of the water, thin clouds, and shadow pixels observed in Fig 10a, c, and
 378 e is equal to the number of water, thin clouds, and shadow pixels at the end of step 1 (Fig. 7f). When
 379 V_{max} is reached at band 4 (red) (Fig. 10 a, b), shadow pixels and thin clouds are removed if $\rho_{rc}(1)$ is
 380 higher than $-0.14 * \rho_{rc}(6) / \rho_{rc}(2) + 0.16$. This condition allows 69% of the shadow pixels over turbid waters,
 381 and 50% of the few remaining thin clouds to be removed. The remaining shadow pixels are observed in

382 a restricted area of the $V(\rho_{rc}(4))$ vs. $\rho_{rc}(4)/\rho_{rc}(2)$ space (Fig. 10b) where there is a risk of confusion. A
383 flag, indicating the potential presence of cloud shadows over water pixels, can be raised when the pixel
384 belongs to this restricted space. When V_{max} is reached at band 3 (green) (Fig. 10 c, d) or 2 (blue) (Fig. 10
385 e, f), shadow pixels and thin clouds are removed after the application of three or seven complementary
386 criteria as defined in Fig. 6, respectively. In contrast to turbid waters, where the maximum of ρ_{rc} is
387 generally observed in the red, extraction of shadow pixels over green and blue waters is more challenging.
388 For instance, only 40% and 30% of shadow pixels over green and blue waters have been removed by the
389 HSV approach, respectively. However, these relatively clear water pixels are located in relatively
390 offshore waters, especially the blue ones, for which the signal over noise ratio of OLI prevents the
391 exploitation of this signal for bio-optical applications. The full processing (i. e. step 1 + step 2) of the
392 image collected over a complex aquaculture area discussed previously (Fig. 8), and not used in the
393 development data set, is now provided in Fig. 11. Cloud shadow pixels, falsely identified as water pixels
394 after the application of the spectral shape analysis (Fig. 11a), are now well classified at the second step
395 of the algorithm (Fig. 11b).

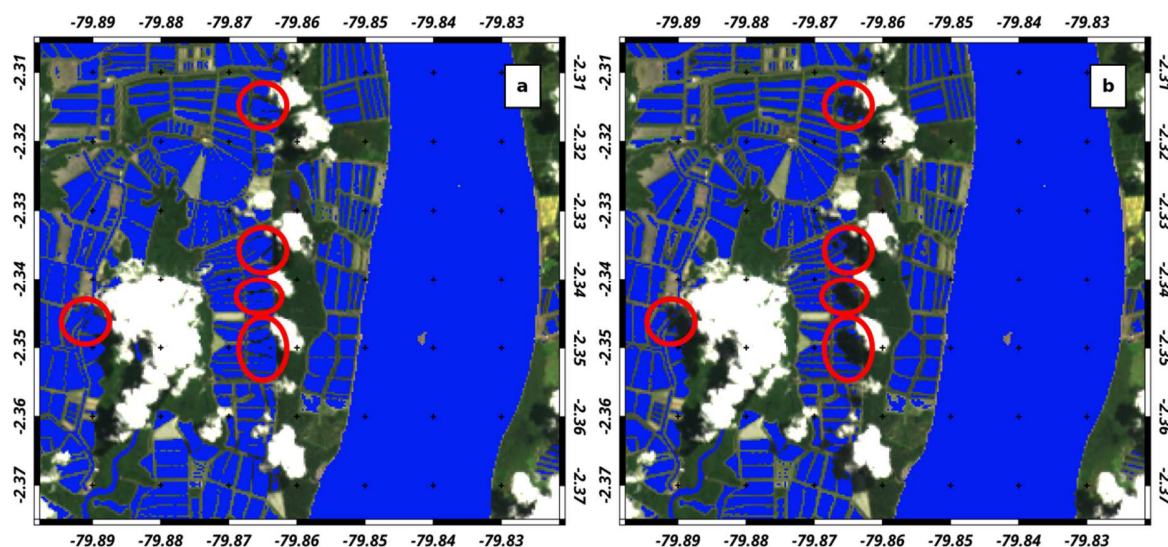
396



397

398 **Fig. 10.** Scatter plots of the Value component as a function of the Saturation component in the red (panels
 399 a and b), green (panels c and d), and blue (panels e and f) for the water (blue dots) and shadow pixels
 400 above water (black dots). The number of pixels before (panels a, c, and e) and after (panels b, d, and f)
 401 the application of each criterion adopted in steps 2.1, 2.2, and 2.3 are provided in each panel.

402



403

404 **Fig. 11.** (a) Water pixel extraction (in blue) after the application of the first step of the algorithm over
 405 the aquaculture area at Rio Guayas presented in Fig. 8. (b) as (a) but after the application of the second
 406 step of the algorithm showing the identification of the cloud shadow pixels over water. See Fig. 8 for the
 407 RGB image.

408

409 **4. Application of WiPE to OLI and comparison with Fmask over contrasted water bodies**

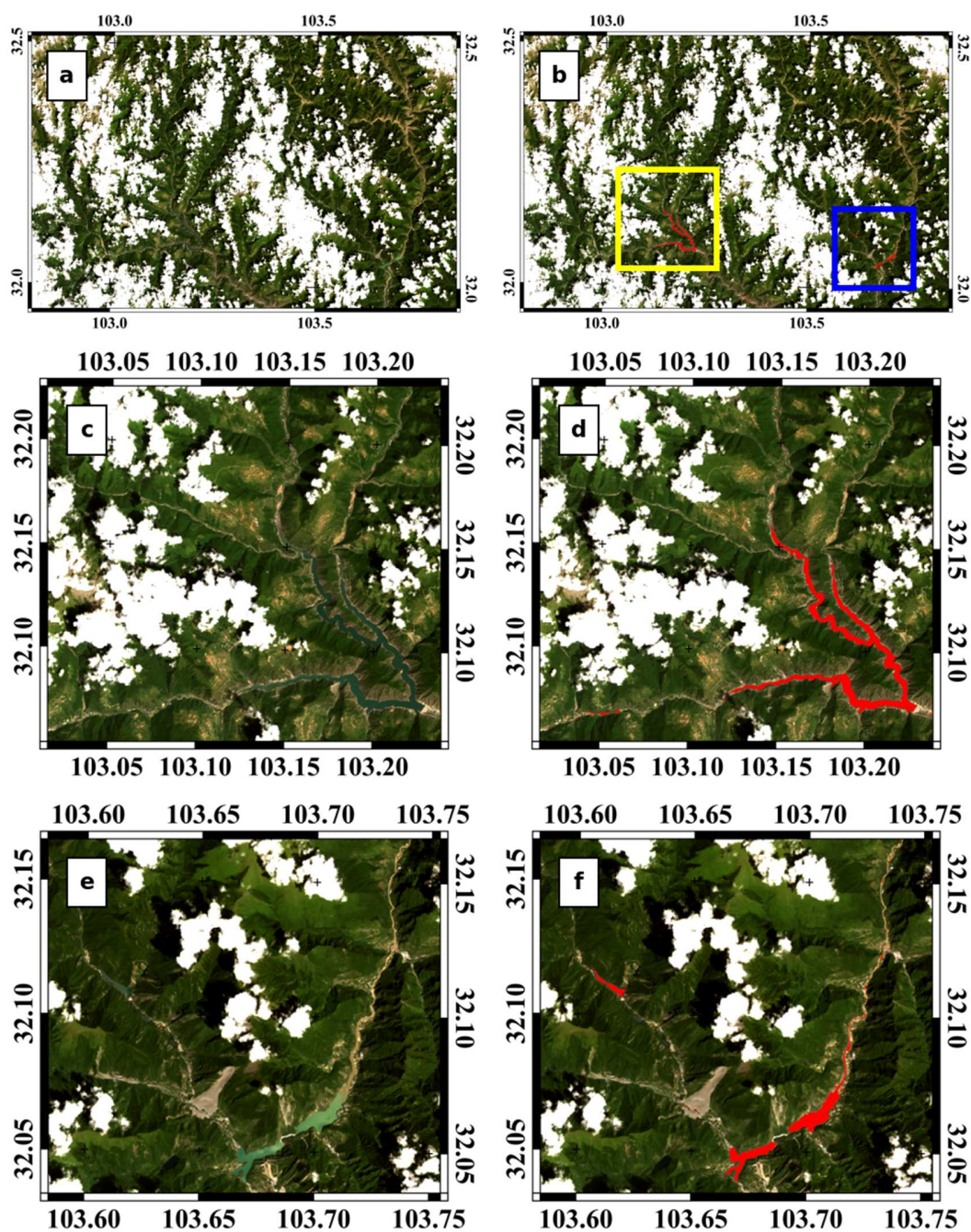
410

411 The WiPE algorithm is based on the use of spectral relationships empirically established on a
 412 given development data set, and cannot, by essence, account adequately for all situations encountered,
 413 especially for mixed situations (i. e. flooded land, clouds and clouds shadow boundaries, bottom albedo
 414 in very clear shallow waters, mountain areas, etc). For example, the spectral shape of $\rho_{rc}(\lambda)$ over water
 415 pixels can also be affected by the bottom albedo in very clear shallow waters, especially in the blue and
 416 green parts of the spectrum. While the differentiation between cloud (or land) and water pixels should
 417 not be affected by the bottom albedo due to the relatively low water reflectance compared to the cloud

418 (or land) reflectances, this may represent an issue for masking shadow and thin clouds pixels over water.
419 This issue can only be addressed by adding a flag cautioning for potential confusion in the processing
420 scheme for clear and very shallow aquatic environment. Adjacency effects may also be another source
421 of uncertainty in the border areas between different objects. The detection of water pixels in mountain
422 areas is also very challenging, due to numerous shadow areas and adjacency effects. The application of
423 WiPE to a complex mountain area in the North West of China shows however that water pixels are still
424 well identified in such complex environment (Fig. 12).

425

426



427

428 Fig. 12 (a) RGB image over a complex mountain area in the North West of China (15/08/2018). (b)

429 Results of the WiPE algorithm with the detected water pixels appear in red. Each of the colored squares

430 represent the two areas where water pixels have been detected. (c) RGB zoom on the region delimited

431 by the yellow square. (d) Result of the WiPE algorithm on the region in (c). (e) and (f) as (c) and (d) but

432 for the region delimited by the red square.

433

434 Being aware of these specific and complex situations, the performance and limitation of the WiPE
435 algorithm are now addressed in details using the second data set gathering images collected by the OLI
436 sensor over contrasted coastal and inland environments. For each selected image, a reference water pixels
437 map (referred to as the reference WPM hereafter) was derived as follows. First the WiPE algorithm has
438 been applied on the image. Then, based on a visual analysis of the image, polygons have been drawn
439 using the QGIS software on the missing water pixels areas (P1) as well as on the areas where WiPE
440 wrongly classify pixels as water pixels (P2). The reference WPM for each image is then generated using
441 the results of WiPE corrected by adding (removing) water pixels from the P1 (P2) polygons. The Mean
442 Absolute Percentage Difference (MAPD) is then calculated between the reference number of water pixels
443 (WPM), and the number of water pixels generated by WiPE and Fmask (Table 2).

444 .

445 The evaluation of WiPE, and the inter-comparison with Fmask (version 3.3) have been performed
446 over the whole validation data set (Table 2), but illustrations are only provided for some representative
447 areas extracted from 6 different scenes and presenting a large range of complex situations (Fig. 13-18).
448 For the 12 complete scenes used for the validation, the MAPD values range between 0.005 and 6% for
449 WiPE. Over the six examined sub-scenes, the highest MAPD value of 11% was related to the presence
450 of thin clouds. The MAPD present higher values for Fmask than for WiPE, with a general tendency for
451 Fmask to under-estimate the number of water pixels, mainly in the presence of turbid waters. Note that
452 for three of the twelve tested scenes, Fmask does not provide any possible solution. Similarly to Fmask,
453 the distinction between water pixels and clouds, as well as between vegetation/land/barren land and water
454 pixels are generally well performed by WiPE (Figs. 13-17). The main differences between the two
455 algorithms are observed over very turbid waters (Figs. 13-14), cloud shadows over waters (Figs. 13, 15,
456 16, 17), and complex coastal environments (Fig. 18).

457 Table 2. Performance of the WiPE and Fmask algorithms on the validation data set. The number of water
458 pixels identified by Fmask, WiPE, and “visual” interpretation (see text) are used to calculate the Mean

459 Absolute Percentage Difference (MAPD in %). The number are given for the whole 12 considered scenes,
 460 while the number between brackets are those obtained over the 6 different sub-scenes provided in Figs.
 461 13-18.

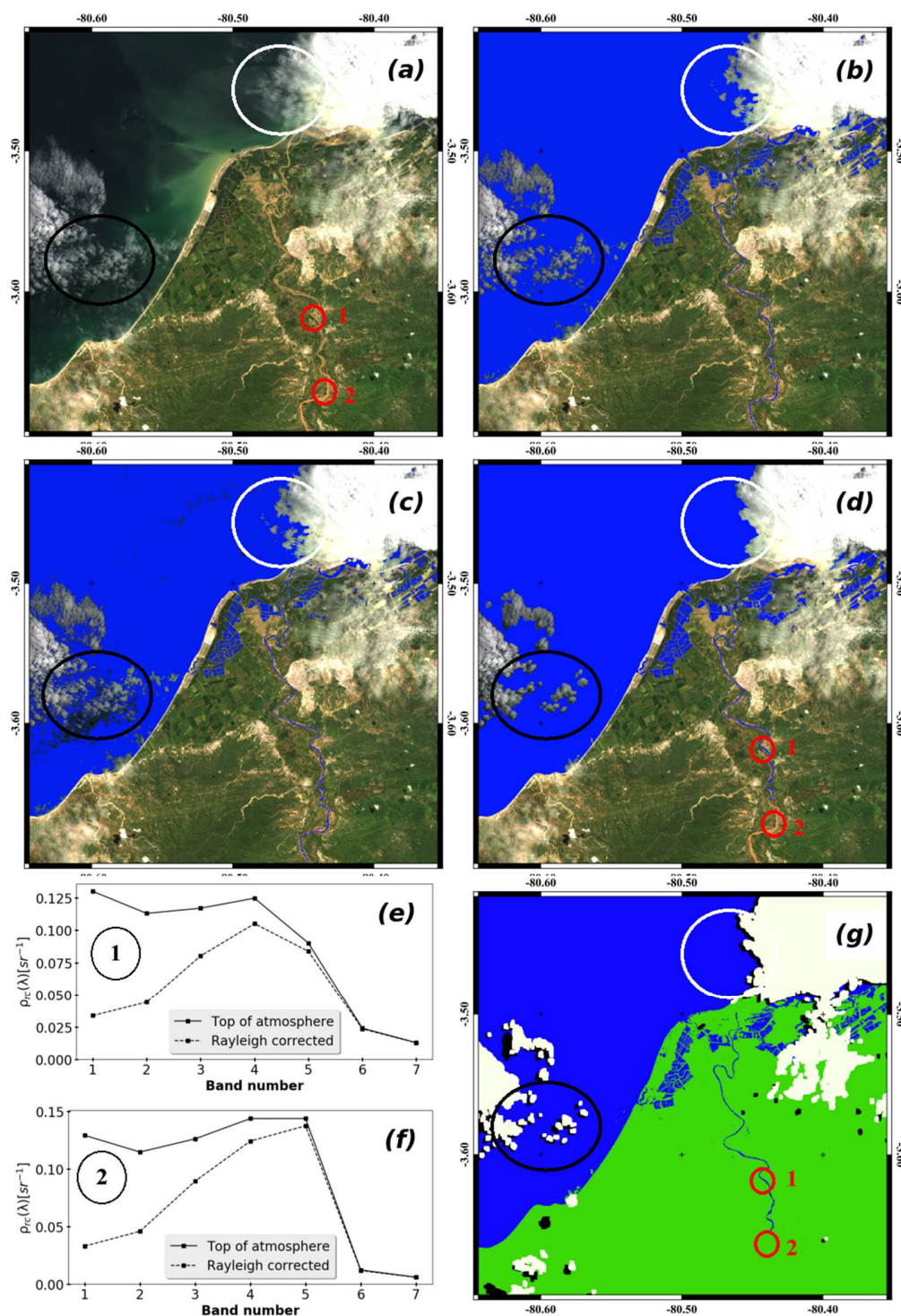
Figure N°	Fmask (water pixel)	WiPE (water pixel)	Visual interpretation	MAPD_Fmask (%)	MAPD_WiPE (%)
Name: LC80110622015137LGN00 Location: Rio Guayas, Ecuador					
13	11,761,455	12,525,625	12,400,369	5.15 (7.8)	1.01 (0.005)
Name: LC81180392015039LGN00 Location: Hangzhou Bay, China					
14	1,810,769	6,862,337	6,793,712	73.35 (87.74)	1.01 (0.006)
Name: LC82330542015220LGN00 Location: Rio Grande, Venezuela					
15	4,181,740	4,287,095	4,244,224	1.47 (14)	1.01 (11)
Name: LC80200242014261LGN00 Location: Moose River, Canada					
16	7,829,913	11,161,707	10,938,473	28.42 (24.6)	2.04 (0.04)
Name: LC81360452015293LGN00 Location: Meghna River Estuary, Bangladesh					
17	25,151,428	25,330,607	25,254,615	0.41 (12.3)	0.30 (0.005)
Name: LC81220442015291LGN00 Location: Zhujiang River, China					
18	4,824,260	4,247,824	4,162,868	15.89 (28.1)	2.04 (0.08)
Name: LC81230512016045LGN00 Location: Center East Sea, Vietnam					
	NA	28813483	27949071	NA	3.09
Name: LC81480452015153LGN00 Location: Gulf of Khambhat, India					
	1,872,122	5,436,606	5,408,972	65.39	0.51
Name: LC82040522015305LGN00 Location: Geba River Estuary, Guinea-Bissau					
	12,859,652	16,041,540	15,602,484	17.58	2.81
Name: LC82240842015061LGN00 Location: Rio de La Plata, Argentina-Uruguay					
	NA	11623842	12408451	NA	6.32
Name: LC82250602014321LGN00 Location: Rio Amazonas, Brazil					
	3,094,867	5,073,280	4,933,148	37.26	2.84
Name: LC81230522016045LGN00 Location: Center East Sea, Vietnam					
	NA	25,447,149	25,632,556	NA	0.72

462

463 The image acquired over the Rio Guayas (Fig. 13) shows that while the two approaches provide
 464 relatively good results over most of the image (MAPD of 7.8% and 0.005% for Fmask and WiPE,
 465 respectively), only WiPE is able to extract very turbid water pixels as those encountered far from the

466 river mouth (red circle n°2 in Fig. 13). From the river mouth to the upper part of the river, the maximum
467 value of the $\rho_{rc}(\lambda)$ spectrum, driven by the water leaving signal, shifts from the green (Fig. 13e) to the
468 near-infrared (Fig. 13f), a typical spectral behavior observed when the water turbidity increases (Han et
469 al., 2016). This pattern is observed over different scenes where the $\rho_{rc}(\lambda)$ spectra peak in the near-infrared,
470 as the one provided in Fig. 14 showing part of the Hangzhou bay where the Qiantang river, characterized
471 by high concentration of sediment, flows (Xie et al., 2013). For this specific image, almost all “true”
472 water pixels are detected as land pixels by Fmask (MAPD = 87.7%), and few of them, probably partly
473 due to the low temperature (5°C), as snow pixels (Fig. 14). In contrast, WiPE is able to identify properly
474 water pixels over the whole scene (MAPD=0.006%). The areas where turbid water pixels are falsely
475 identified as land by Fmask present a $\rho_{rc}(\lambda)$ spectrum with a maximum in the near-infrared (Fig. 14f).
476 The very few water pixels which are correctly detected by Fmask over this very turbid area are those for
477 which the maximum $\rho_{rc}(\lambda)$ values are reached in band 4 (see red circle n°1 in Fig. 14e) or band 3 as for
478 the water pixels in the bottom left corner of Fig. 14g. For low turbidity level, where the $\rho_{rc}(\lambda)$ maximum
479 values are not reached in the near-infrared (band 5), water pixels are generally well detected by the two
480 different algorithms (Fig. 13, 15-18). As mentioned by Zhu and Woodcock (2012), the adopted threshold
481 procedure for the detection of water bodies from Fmask works well for most water bodies but may fail
482 over cold (compared to surrounding areas) and bright (i.e. turbid) pixels. For this reason, and in a similar
483 way to the procedure applied for the detection of clouds in land areas, the last version of Fmask uses a
484 dynamic threshold for detecting clouds in water areas (Zhu et al. 2015). While such dynamical approach
485 provides better cloud detection over water areas (Zhu et al. 2015), the present study shows that detection
486 of water pixels over very turbid waters, where the maximum $\rho_{rc}(\lambda)$ value is observed at band 5, is still
487 not satisfactory. The dynamic threshold procedure used in Fmask should then be adapted for such
488 environments.

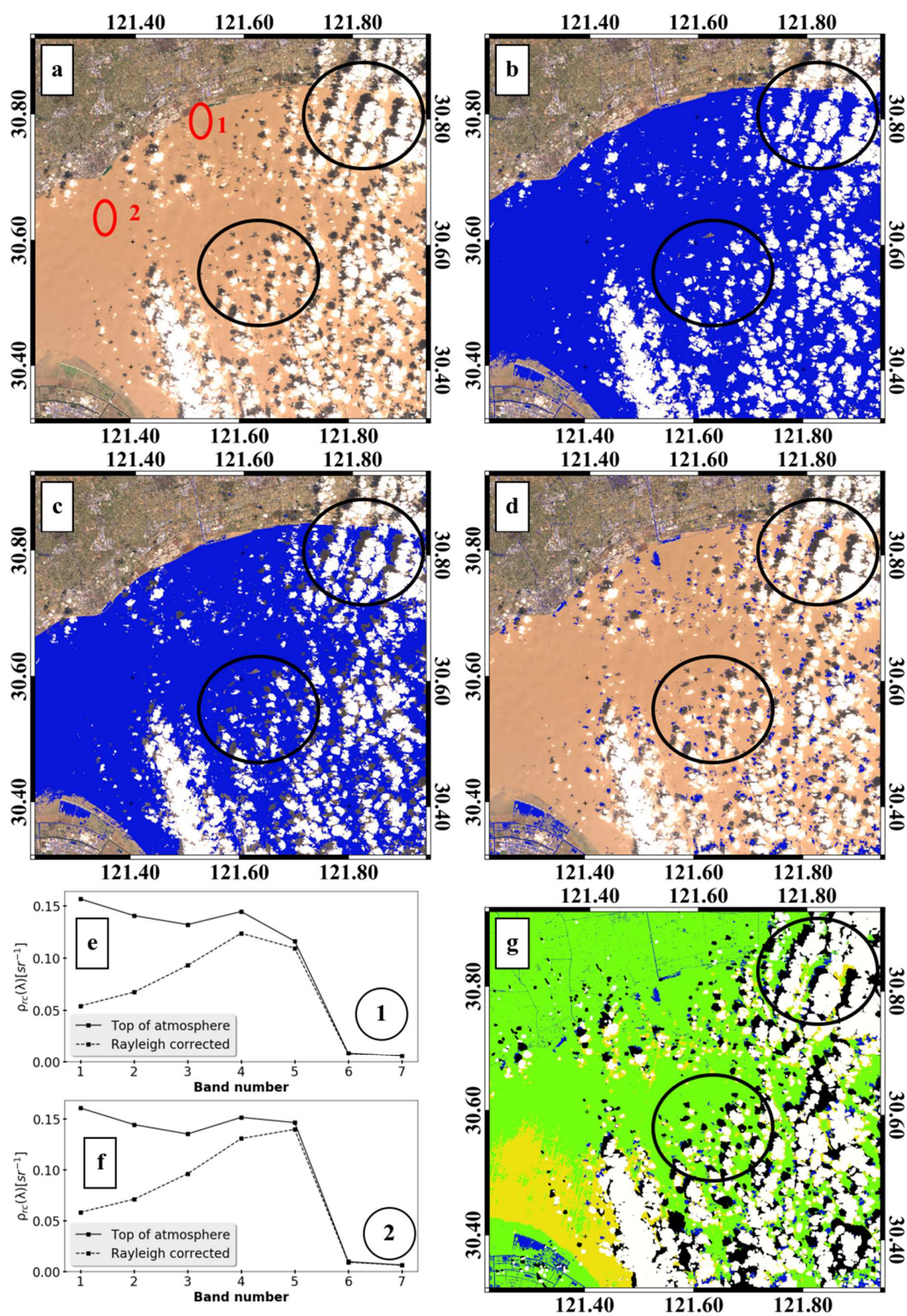
489 All images show that the detection of shadow pixels over water increases after the application of
490 the HSV-space based criteria (i.e. the second step of WiPE). While some “true” shadow pixels are
491 considered as water after the application of the first step of the algorithm (black circles in panels b of
492 Figures 13, 14, 16, 17), they are correctly identified as shadow after the second step (black circles in
493 panels c of Fig. 13, 14, 16, 17). The detection of thin clouds, especially over clear waters, seems to be
494 slightly underestimated by WiPE (already discussed in section 3.2) and Fmask (see white circles Figure
495 13). Cloud masking is usually well performed by the two different approaches. However, while the new
496 approach tends to slightly under-estimate the cloud shadow areas in favor of water pixels, Fmask tends
497 to over-estimate cloud shadow areas. Cloud shadow pixels which are classified as water by the new
498 approach are those belonging to the confusing area in the V-S space (Fig. 10). An example of wrong
499 shadow pixel identification by WiPE is provided in Fig. 15 (black circles). These pixels, which are
500 characterized by a $\rho_{rc}(\lambda)$ maximum in the red (channel 4), present V and S values around 0.12, and 0.26,
501 respectively, and are therefore classify as belonging to the confusing space, for which a flag could be
502 raised during the image processing. In the same way, Fmask, which provides relatively good estimates
503 of cloud shadows, may falsely classify cloud shadows as water pixels, especially when the shadow area
504 is located over land (Fig. 16) and barren land (Fig. 18). Over very complex areas such as the harbor area
505 of the outlet of the Zhujiang river in China (Fig. 18) the new algorithm performs remarkably well. Fine
506 structures like harbor protections in water are identified. Misclassification of construction as cloud by
507 Fmask may also occur (the southern part of the image in Fig. 18), resulting in a detection of false shadow
508 pixels over water areas.



509

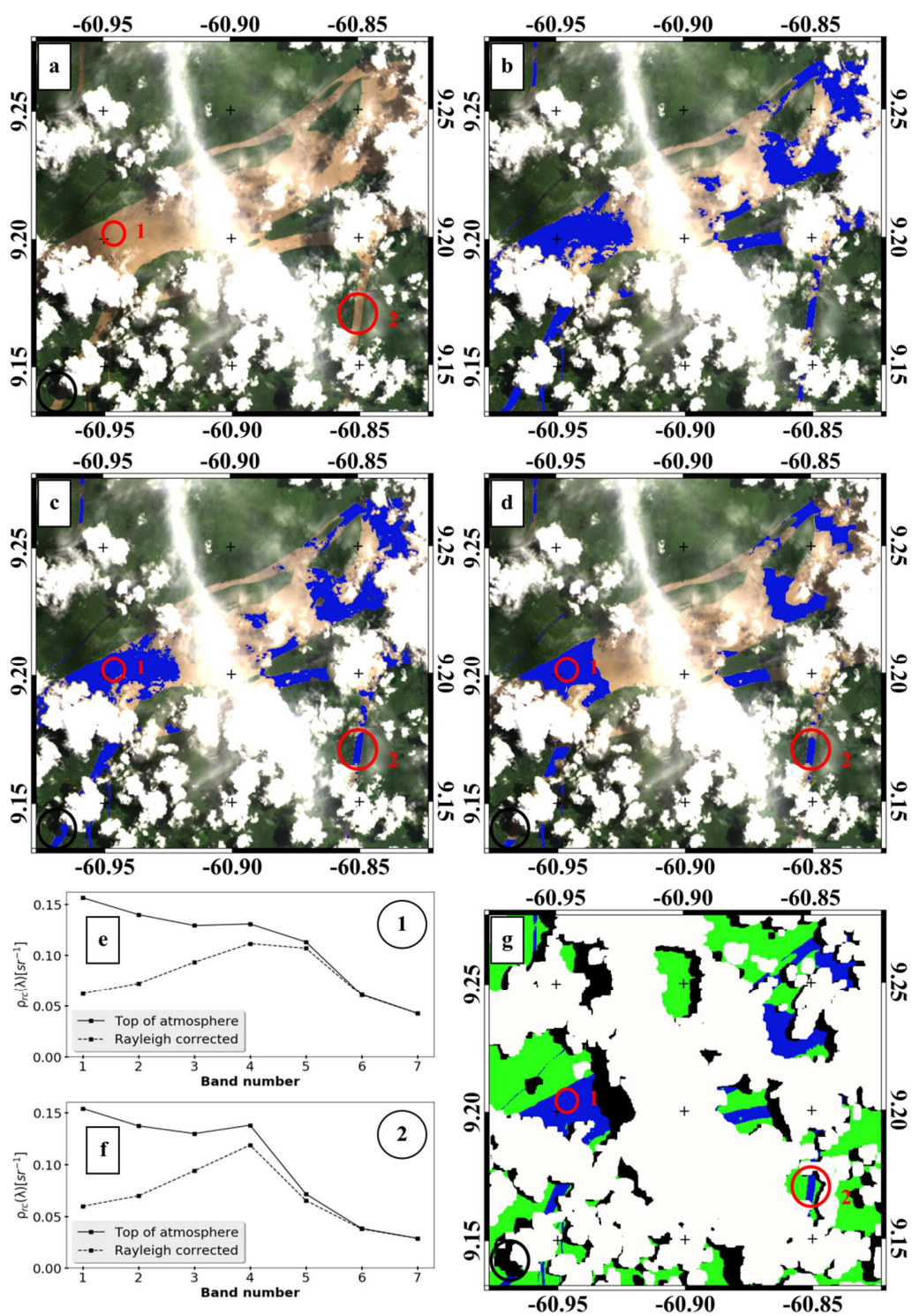
510 **Fig. 13.** (a) RGB image over the Rio Guayas (Ecuador, 17/05/2015). Results of the water pixel extraction
 511 (in blue) after the first (b) and second (c) steps of the new algorithm and of Fmask (d). (e and f) $\rho_{rc}(\lambda)$
 512 spectra extracted over the two identified sub-pixels identified by red circles. (g) as (d) but showing the
 513 results of Fmask using a color code for water (blue), land (green), cloud (white), shadow (black), and

514 snow (yellow). Note that snow is not present in this image. The black and white circles show area of
515 cloud shadow and thin clouds (see text).



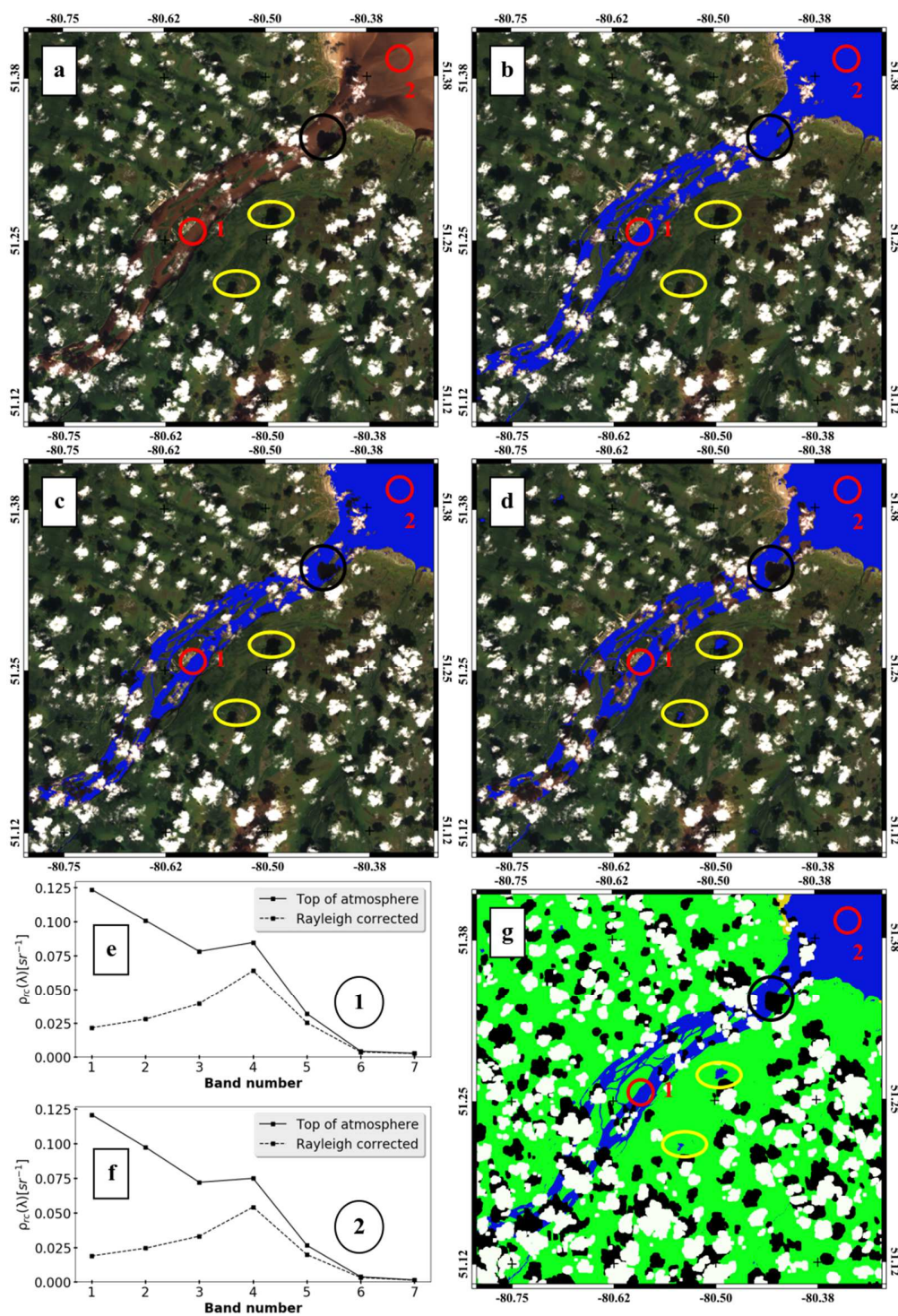
516

517 **Fig. 14.** As Fig. 13 but for the Hangzhou bay (China, 08/02/2015).



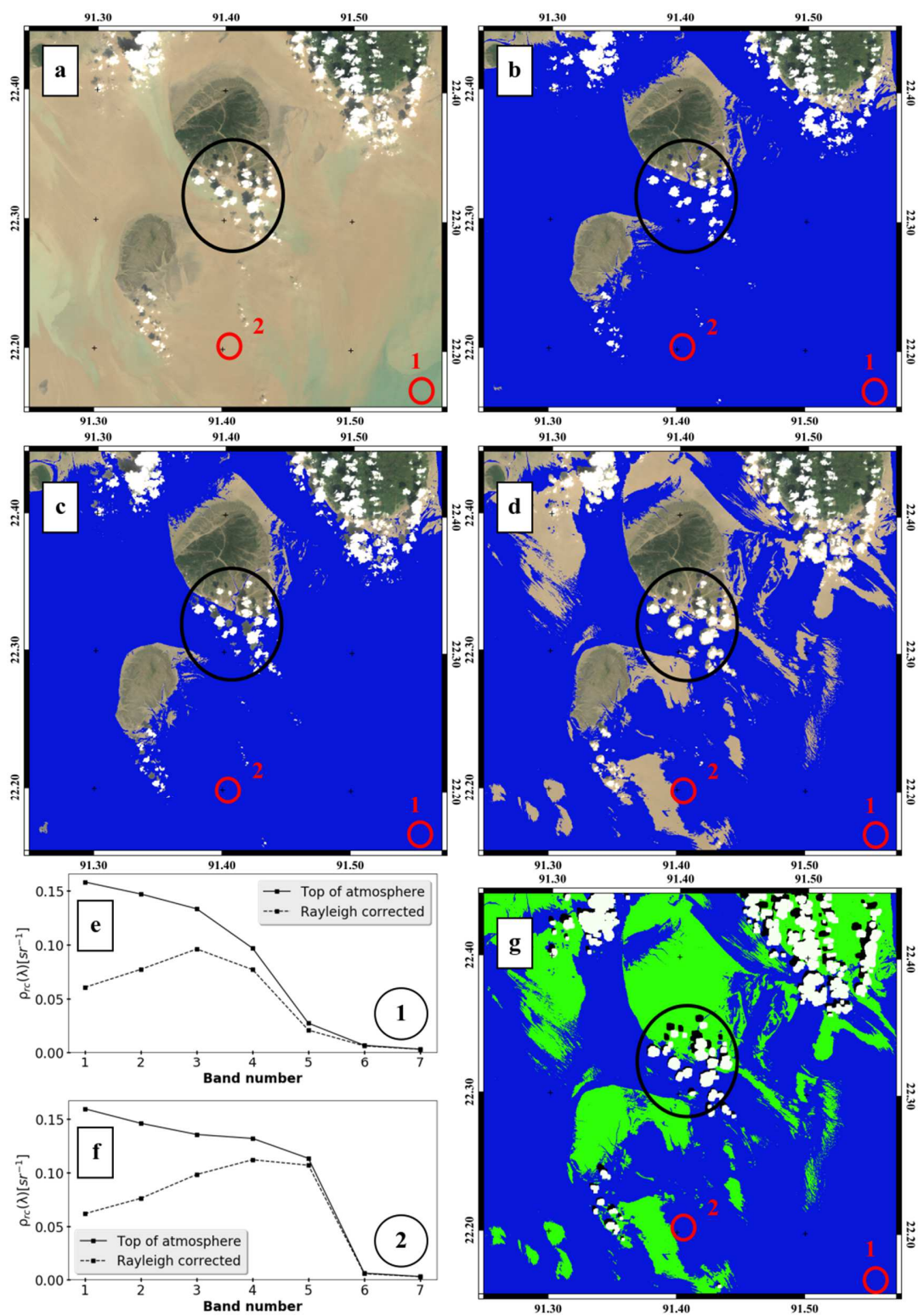
518

519 **Fig. 15.** As Fig. 13 but for the Rio Grande (Venezuela, 17/11/2014)



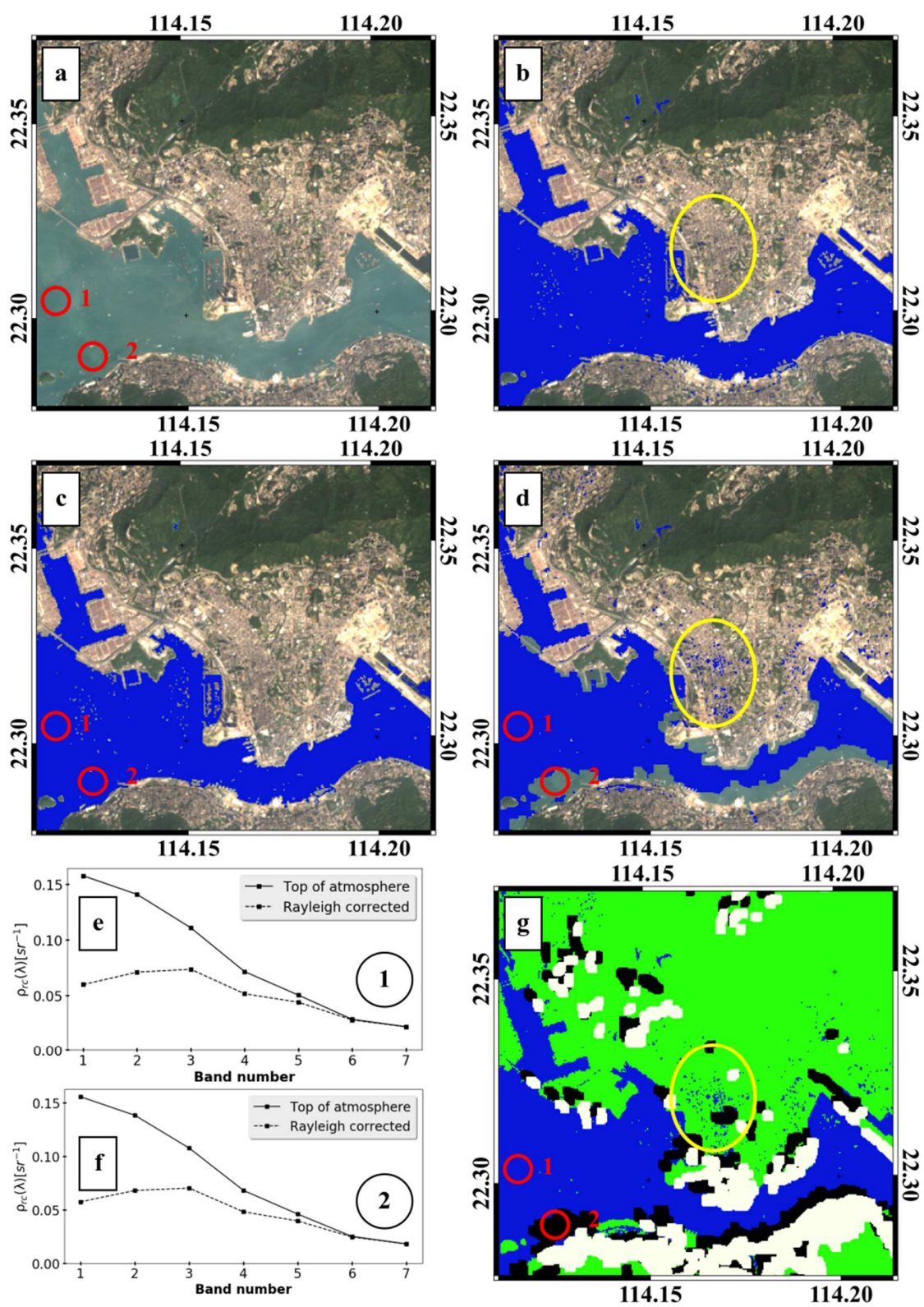
520

521 **Fig. 16.** As Fig. 13 but for the Moose river (Canada, 18/09/2014). The yellow circles show land areas
 522 identified as water by Fmask, the black circle shows a cloud shadow area, and red circles delimit the
 523 water areas where the $\rho_{rc}(\lambda)$ spectra 1 (e) and 2 (f) are extracted (see text).



524

525 **Fig. 17.** As Fig. 13 but for the Maghna estuary (Bangladesh, 20/10/2015)



526

527 **Fig. 18.** As Fig. 13 but for the Hong Kong bay (China, 18/10/2015).

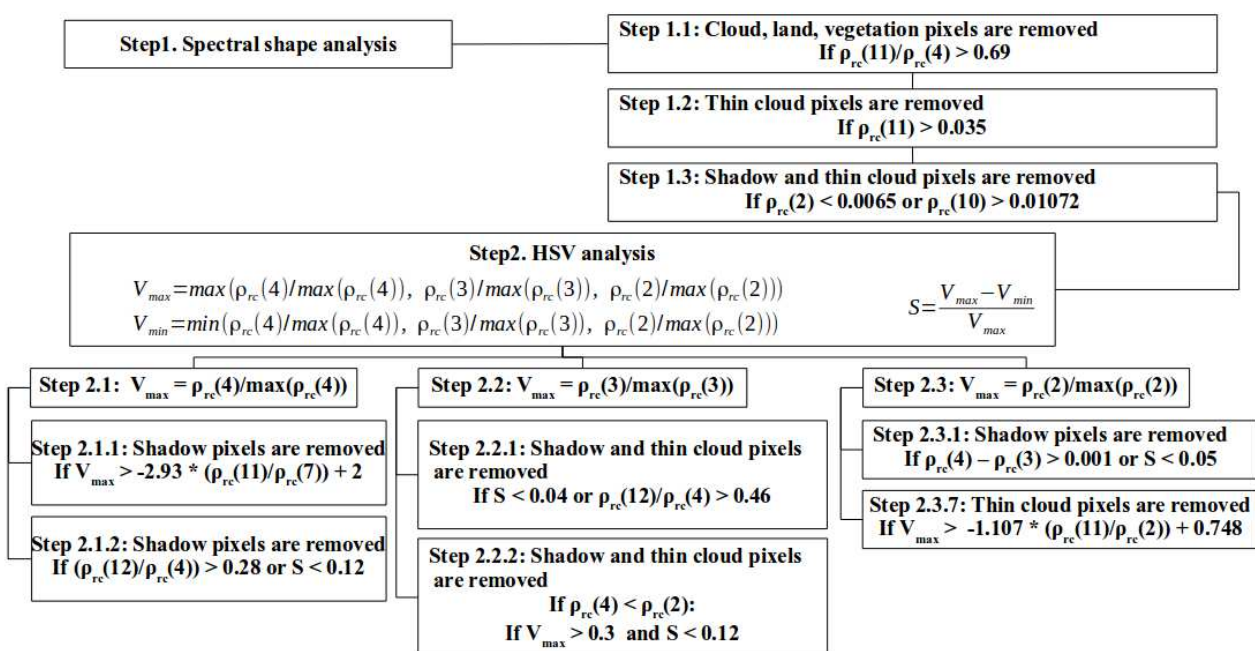
528

529 **5. Adaptation of WiPE for MSI on Sentinel 2a**

530

531 The WiPE algorithm, originally developed for L8-OLI, has been adapted to S2a-MSI using the
 532 seven following spectral bands: bands 2 (496.6 nm), 3 (560 nm), 4 (664.5 nm), 7 (782.5 nm), 10 (1373.5
 533 nm), 11 (1613.7 nm), and 12 (2202.4 nm). The same methodology used to develop WiPE for L8-OLI,
 534 has been adopted for S2a-MSI. The two steps are both applied to the Rayleigh corrected reflectance. The
 535 first step is dedicated to the removal of barren land, construction, vegetation, clouds and a minority of
 536 thin clouds and clouds shadows. The second step, based on the HSV transformation, is dedicated to the
 537 removal of the remaining thin clouds and cloud shadows. Similar results as those obtained for L8-OLI
 538 have been obtained in terms of water pixel extraction, as demonstrated by the complex image of an
 539 aquaculture area in the Huangmao river estuary in China (Fig. 20) or over the Tonle Sap in Cambodia
 540 (Fig. 21). It is worth to notice that, thanks to the high spatial resolution of MSI, fish cages present in the
 541 Huangmao river estuary illustration map are well detected and not mixed with water pixels (Fig. 20d).

542



543

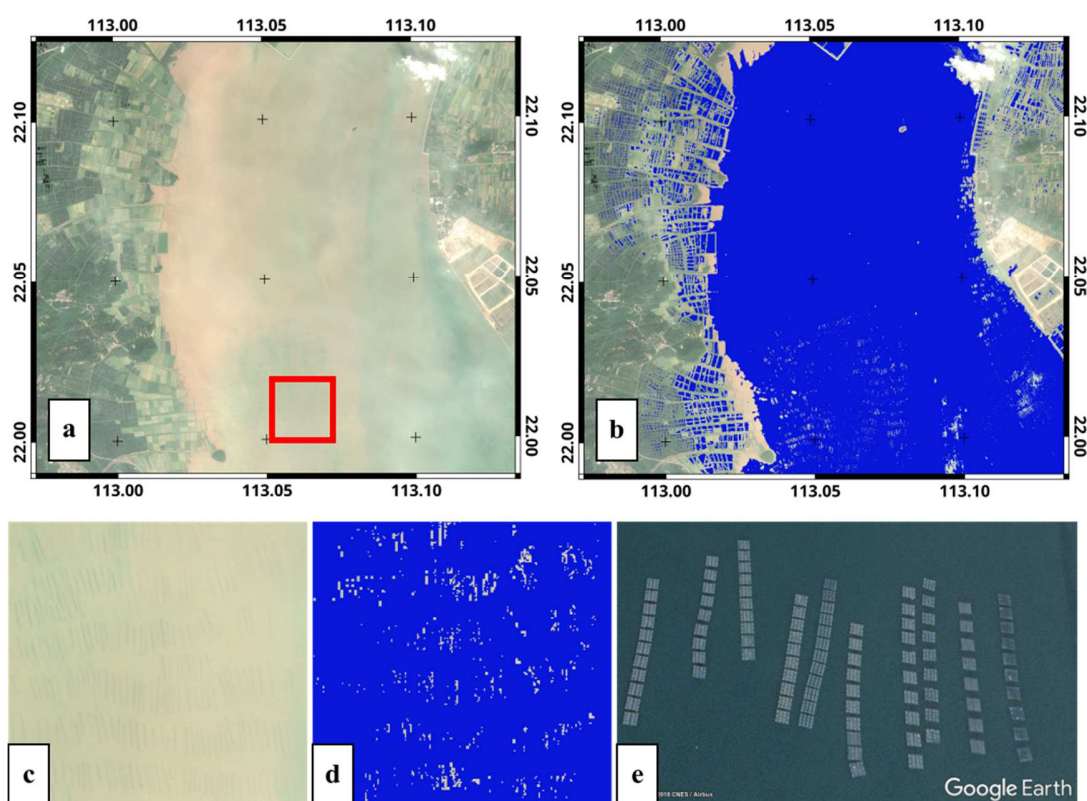
544 **Fig. 19.** The logic flow of the water extraction pixel algorithm based on the combination of spectral shape
 545 analysis (step 1) and HSV analysis (step 2) for the S2a-MSI sensor. This flowchart requires the Rayleigh
 546 corrected reflectance (Eq.11) at bands 2, 3, 4, 7, 10, 11, and 12 as input parameters.

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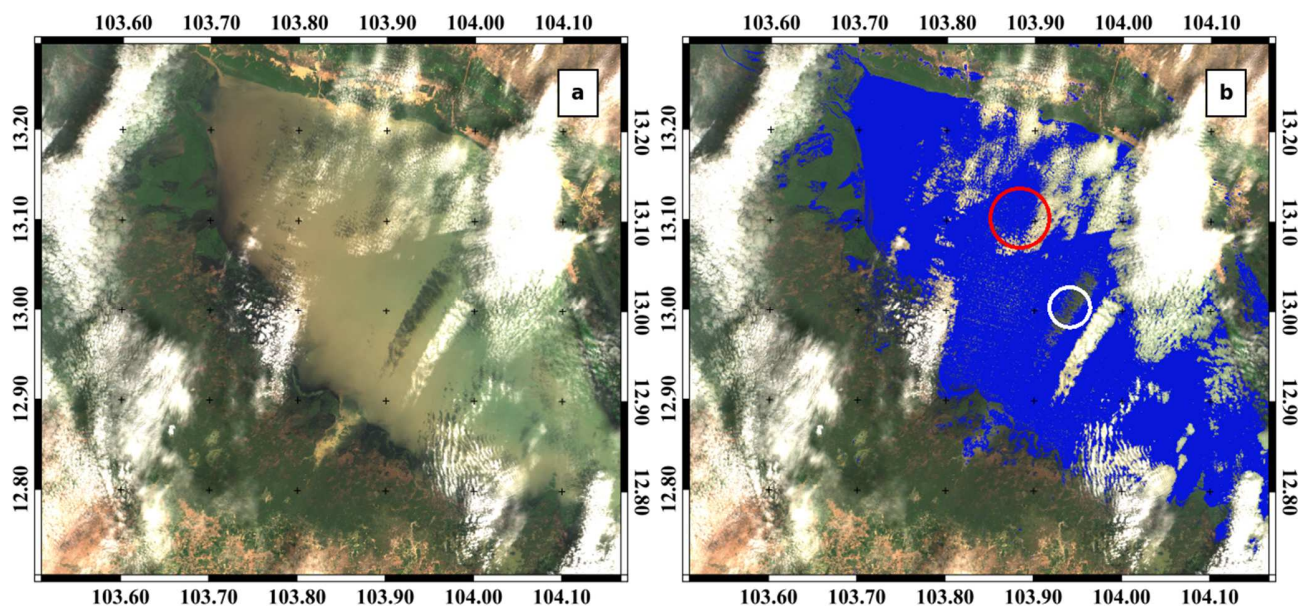
551

552 **Fig. 20.** (a) RGB image over the Huangmao river estuary in China. (b) Results of the water pixel
 553 extraction by WiPE. (c) Zoom of the area framed in red (a) showing the fish cages which are also
 554 identified with WiPE in (b) and zoomed in (d). (e) Fishes cages showed from Google Earth image.

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559 **Fig. 21.** (a) RGB image over the Tonle Sap in Cambodia. (b) Results of the water pixel extraction by
 560 WiPE. The white and red circles indicate situations with correct and wrong cloud shadows identification,
 561 respectively.

562

563 In contrast to L8-OLI for which the spatial resolution of all bands is the same and equal to 30
 564 meters, the spatial resolution of the algorithm-required bands for S2a-MSI are equal to 10 (bands 2, 3,
 565 and 4), 20 (7, 11, and 12), and 60 (band 10) meters. These different spatial resolutions introduce some
 566 artefacts in the extraction of water pixels, especially at the border of objects under strong contrast, such
 567 as cloud shadow in the immediate proximity of clouds. This is clearly illustrated in Fig. 21 where cloud
 568 shadows are well detected when they are relatively far from the cloud (white circle in Fig. 21b), and not
 569 detected when they are at the very border of the clouds (red circle in Fig. 21b). Future works are therefore
 570 needed to figure this specific issue out.

571

572 **6. Concluding remarks**

573 Remote sensing is a major observation tool for estimating surface water areas for many
574 environmental and economical applications (aquaculture, flooding survey, water management, etc). In
575 addition to this quantification aspect of surface water bodies, the detection of water pixels from remote
576 sensing observations is an essential and critical step before the application of adapted algorithms aiming
577 at estimating parameters describing the biogeochemical status of surface water bodies from space. A new
578 algorithm (referred as WiPE) has been developed to assess water pixels from L8-OLI, and has been
579 adapted for the MSI sensor. Unlike existing algorithm, WiPE is based on the Rayleigh-corrected
580 reflectance, $\rho_{rc}(\lambda)$, which makes it more sensitive to the spectral signature of the different objects
581 considered: clouds, thin clouds, cloud shadow, vegetation, barren land, construction, and water. In
582 contrast to other approaches, such as Fmask, the present algorithm is not able to distinguish the different
583 considered objects individually, but rather to extract water pixels from other pixels. For that purpose, this
584 algorithm consists of two main steps. First, clouds, thin clouds over land, cloud shadow over land,
585 vegetation, barren land, and construction are removed based on a spectral shape analysis of $\rho_{rc}(\lambda)$.
586 Second, the Rayleigh-corrected reflectance spectra are transferred into the HSV color space to improve
587 the distinction between water pixels and thin cloud and shadow pixels over water areas not affected by
588 sun glint. This second step is based on the contrast of the whole image, and does not require any
589 knowledge on the position and altitude of clouds. The present algorithm generally shows very good
590 performance for the detection of water pixels over complex aquatic environments, especially in very
591 turbid areas where the maximum of $\rho_{rc}(\lambda)$ is observed in the near-infrared. The main limitation of the
592 approach is for the detection of cloud shadow over blue to green waters where a confusion between cloud
593 shadow pixels and water pixels may occur. As WiPE does not make any assumption on the
594 presence/absence of clouds and then on the potential location of areas affected by cloud shadow, future
595 improvement of the method could account for the proximity of clouds.

596

597

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