MAPPING BENTHOS, BATHYMETRY AND WATER CONSTITUENTS OF INLAND WATERS USING LANDSAT 8 - A CASE STUDY AT LAKE KUMMEROW NEAR ROSTOCK

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Abstract

Coastal and inland waters are threatened by multiple stressors such as climate change, eutrophication, contamination and degradation. Benthic macrophytes and water constituents are sensitive to environmental changes; they therefore represent key biological indicators for assessing the ecological state of water bodies within the European Water Framework Directive. Today, monitoring macrophytes and water constituents is still based on point based *in situ* mappings which cannot capture temporal and spatial dynamics. Satellite remote sensing, however, offers larger spatial coverage and higher temporal frequency for monitoring. Due to its improved radiometric and spectral resolution as well as signal-to-noise ratio the Landsat 8 OLI sensor is expected to be well-suited for remote sensing of water bodies. Bio-optical models relate the reflectance of a water body to concentrations of water constituents, benthos and water depths by means of radiative transfer. Within the project LAKESAT we tested the potential of Landsat 8 for mapping benthic macrophytes, bathymetry and water constituents at a test site in Mecklenburg-Western Pomerania, Northern Germany. We applied the bio-optical model WASI-2D to a scene acquired on 19th July 2014 at Lake Kummerow (53.808° N, 12.856° E). Concurrently taken water samples and submersible spectroradiometer measurements served to parameterise WASI-2D. Inverse modelling of the Landsat 8 reflectance spectra allowed deriving concentrations of chlorophyll a, suspended particulate matter and coloured dissolved organic matter in optically deep water; bathymetry and fractional coverage of bottom substrate via spectral endmembers, i.e. sandy sediment and dominant macrophytes (*Potamogeton spp.*) were retrieved in optically shallow parts of the lake. Chlorophyll a concentrations ($<0.1 \pm 0.76\ \mu g l^{-1}$) and absorption by coloured dissolved organic matter ($0.71 \pm 0.13\ m^{-1}$) were low on average. Suspended particulate matter concentrations ($7.21 \pm 1.68\ mg l^{-1}$) were slightly higher compared to analysed water samples. Benthos mappings showed predominating coverages of sandy sediment and single spots with dense macrophyte coverage which corresponds with visual observations. Landsat 8 derived bathymetry ranged between 0 and 1.6 m which matches with the official bathymetry chart. The results indicate that Landsat 8 is suitable for mapping water constituents, water depths and benthos and encourage to further take effort in using satellite data for lake monitoring.

1. INTRODUCTION

Climate and global change strongly affect ecological functions of inland waters and their ecosystem services [1]. Lakes respond to climate change with physical, chemical and biological changes [2]. Physical, chemical and biological quality elements of lakes form the basis for assessing and monitoring their ecological states within the European Water Framework Directive (WFD, [3]). Within WFD monitoring submerged macrophytes is a key biological quality element [4]. To gather their abundance and spatial extent, however, a spatially large-scale approach is necessary. Most EU member states monitor freshwater macrophytes at spatial scales of several 100 m² along diving transects [4, 5] with a mapping interval of three years [3].

Macrophytes regrow in each spring. Changes in the lake environment such as temperature, water level and water transparency, however, may affect their inter- and inner-annual abundance which remain undetected under the current monitoring scheme. Moreover, spatially and temporally highly variable water constituents such as phytoplankton and sediment load (turbidity) are subject to the WFD monitoring to assess the ecological state of lakes. Water samplings are therefore taken at least every two months on a spatial scale < 20 m² [5]. This sampling scheme, however, can hardly detect rapidly occurring algal blooms [6].

For WFD monitoring satellite remote sensing offers a greater spatial coverage and higher temporal frequency. Mapping submerged macrophytes and water constituents by remote sensing is still challenging [7, 8]. In optically deep water (reflectance originates from the water column) optically active constituents such as chlorophyll-a of phytoplankton (Chl-a), coloured dissolved organic matter (CDOM) or suspended particulate matter (SPM) characterise lake reflectance; in optically shallow waters where a part of the reflectance originates from the ground, varying bottom coverages and water depths additionally contribute to the signal. Analytical methods such as bio-optical models relate optical water properties to its reflectance by means of radiative transfer [9]. Inverse modelling of water leaving reflectances allows retrieving water depth, constituent concentrations and benthos coverage (e.g. [10]). Bio-optical models, however, require sensors with high radiometric and spectral resolution [7]. New (e.g. Landsat 8) and upcoming sensors (e.g. Sentinel-2 and EnMAP) with improved technology (higher spectral, radiometric and temporal resolution), however, offer a great potential for lake remote sensing and bio-optical modelling.

To improve the assessment and understanding of lake water quality the project LAKESAT aims to develop a processing chain for synergetic use of existing and upcoming sensors. One of the test sites is Lake Kummerow (53.808° N, 12.856° E), a shallow eutrophic lake in Northern Germany. For this lake, we used a Landsat 8 scene (19th July 2014) and the bio-optical modelling tool WASI-2D [11] to map freshwater macrophytes and water depths in optically shallow as well as water constituents (SPM, CDOM, Chl-a) in optically deep water.

2. MATERIALS AND METHODS

2.1. Study area

Lake Kummerow is the eighth largest natural lake of Germany with a surface area of 32.55 km² [12]. Due to its large size it is an important migration and resting area for birds and is further a place for manifold recreational activities. Lake Kummerow therefore is subject to monitoring within the WFD and European bathing water directive. The lake developed as tonguelike basin during the last Weichselian glaciation. With a low average depth of 8.1 m Lake Kumerow (FIG. 1) represents eutrophic inland waters which are sensitive to external factors, i.e. its hinterland, discharge and weather conditions [12, 13].

The lake’s catchment area covers approximately 1,150 km². Agricultural cultivation, grassland and forest are predominant land uses (85 % share) which strongly influence the lake’s nutrient balance [13]. The wind exposed location of the lake guarantees prevailing mixing conditions with a polymictic character and an episodic thermal stratification (Epi-, Meta- and Hypolimnion). Moreover, backwater effects occur due to the low relief gradient between the outflow of river Peene in the north and the Baltic Sea ([12], FIG. 1). Small patches of freshwater macrophytes, mainly *Potamogeton spp.* (i.e. *Potamogeton perfoliatus* and *Potamogeton pectinatus*), occur in the northern shallow waters. Both macrophyte species indicate water with a heavy nutrient load [14]. Sandy sediments (gyttja) form the substrate.

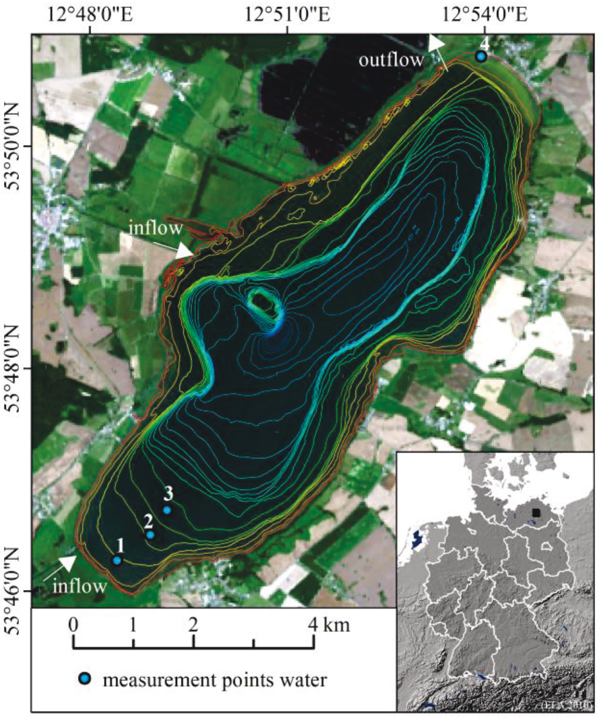

FIG 1. The study area Lake Kummerow. The background shows a Landsat 8 true colour composite (19th July 2014). The bathymetric contours are in 1 m intervals [15]; the blue dots indicate the location of *in situ* sampling points.

2.2. Measurements, data and pre-processing

Lake Kummerow is located within two Landsat 8 paths (193 and 194). A scene acquired by Landsat 8 on 19th of July 2014 (day of year 200) at 12:08 local time (path 194, row 22) served for this study. Clear sky conditions prevailed at the acquisition date. Wind speed was about 2-3 bf and wind direction was north-east. We collected *in situ* data concurrently to the satellite overpass (± 1 hour) at three sampling points in the optically deep water and one sampling point in the optically shallow water close to the shoreline (Fig. 1). Water samples were frozen and analysed in the laboratory (UCL Kiel) for Chl-a (μgl^{-1}, method: DIN 38412 L16), SPM (mgl^{-1}, method: DIN EN 872 H33) and absorption at 436 nm (m^{-1}, method: DIN EN ISO 7887 C1). We also conducted spectroradiometer measurements with submersible RAMSES [16] devices to provide upwelling and downwelling *in situ* irradiance (mWm^{-2}nm^{-1}) of the upper water column (0-70 cm). Further measurements included Secchi depth, surface water temperature, pH and conductivity (TAB 1).

Image pre-processing was carried out with the open-source toolbox BEAM version 5.0 [17]. We used the provisional Landsat 8 OLI reflectance product [18]. Comparisons with *in situ* measured reflectances showed acceptable spectral curves of land surfaces.

Measurement point	1	2	3	4
Chl-a [μgl^{-1}]	5.9	4.4	-	7.4
Phaeophytin [μgl^{-1}]	2.4	1.3	-	3.5
SPM [mgl^{-1}]	3.1	2	-	4.7
$a_{436\ nm}$	6.3	5.9	-	5.6
Secchi depth [m]	1.45	2.00	1.75	Bottom (0.7)
pH	8.5	8.6	8.6	8.3
Temperature [°C]	24.6	24.5	24.7	24.8
Conductivity [μScm^{-1}]	600	590	590	610

TAB 1. Results of *in situ* measurements for the sampling points (point 3 was not analysed in the laboratory).

Since the land reflectance product showed processing artefacts in the lake we additionally modified deep water areas by means of an empirical line correction. To extract the lake area we further masked out land pixels applying the modified normalised difference water index MNDWI [19] with the Landsat 8 bands Green (530-590 nm) and SWIR 1 (1570 – 1650 nm) [20]. The water area (34,631 pixels) was then analysed using the bio-optical tool WASI-2D [11].

2.3. Bio-optical model inversion

In optically deep water scattering and absorption by water constituents, e.g. Chl-a, SPM and CDOM influence lake water reflectance. Additionally, the bottom contributes to the signal in optically shallow water. WASI-2D [11] is a modelling tool to simulate the radiative transfer in both optically shallow and deep waters. To derive water body characteristics, e. g. water constituent concentration, water depth and benthos, WASI-2D combines radiative transfer and bio-optical models by means of spectral inversion. WASI-2D calculates a reflectance spectrum according to a set of constant and variable model parameters (e.g. concentration of SPM, Chl-a, absorption by CDOM, water depth, bottom coverage). The calculated spectrum is compared to the spectrum of a Landsat pixel. For each pixel WASI-2D repeats the calculation of spectra iteratively by varying the variable parameters within a predefined range until a best model fit has been achieved. Modelling terminates when either the residuum, i.e. the difference between measured and calculated spectrum, falls below a predefined threshold value or a predefined maximum number of iterations has been reached [11]. WASI-2D then stores the best or final fit values of the variable model parameters in spatial output files. Additional output files are the residuals and the number of iterations of the best or final fit; thus, bio-optical models enable derivation of water depths and benthic signal [21].

To distinguish between optically deep and shallow water we first applied the deep water reflectance model to the entire lake area. We choose Chl-a, SPM and absorption by CDOM ($a_{CDOM(440nm)}$) for fit parameters (TAB 2). To model remote sensing reflectance we used the model by [22] which is implemented in WASI-2D.

Variable parameters	Start	Min	Max
Chl-a [mgl^{-1}]	1.0	0.0	70.0
SPM [mgl^{-1}]	1.0	0.0	30.0
$a_{CDOM}(_{440nm})$ [m^{-1}]	0.1	0.0	10.0
g_{dd} [sr^{-1}]	0.05	0.01	1.0

TAB 2. Setting of variable model parameters for optically deep water at Lake Kummerow.

Inverse modelling was conducted using Landsat 8 bands coastal/aerosol (430-450 nm), blue (450-510nm), green (530-590 nm) and red (640-670 nm). Therefore the WASI-2D spectral database was resampled to these bands. Pixels which showed the maximum number of iterations (here 1000) were considered as optically shallow water. We assumed that the model fit failed at these pixels as the bottom contributes to the measured reflectance [10]. For these pixels, the shallow water parameterisation was applied in a second step.

For shallow water modelling WASI-2D requires reflectance spectra of benthic substrates as model input. The bottom spectra should represent pure benthic substrate types. They serve as endmembers for a linear unmixing embedded in WASI-2D which allows the retrieval of benthos coverages for each pixel (TAB 3). Defining endmember spectra and the range of variable model parameters are crucial for model performance. The former determines the arrangement of bottom coverages; the latter defines the value range of the model output, because the model is forced to keep the variable parameters within the given boundaries.

Variable parameters	Start	Min	Max
$a_{CDOM(440nm)}$ [m^{-1}]	0.855	0.0	5.0
water depth [m]	0.576	0.0	2.0
coverage *Potamogeton perfoliatus* [%]	0.1	0.0	1.0
coverage sandy sediment [%]	0.9	0.0	1.0
Constant parameters			
Chl-a [mgl^{-1}]	5.00		
SPM [mgl^{-1}]	1.00		

TAB 3. WASI-2D parameter setting for optically shallow water.

For Lake Kummerow we selected two spectral endmembers: sandy sediment from the WASI data base and the freshwater macrophyte *Potamogeton perfoliatus*. The spectrum for *Potamogeton perfoliatus* was derived applying a interpolation model which includes the varying spectral behaviour of macrophytes during the vegetation period [23]. Both spectra were then resampled to the Landsat 8 spectral response curves (FIG 2).

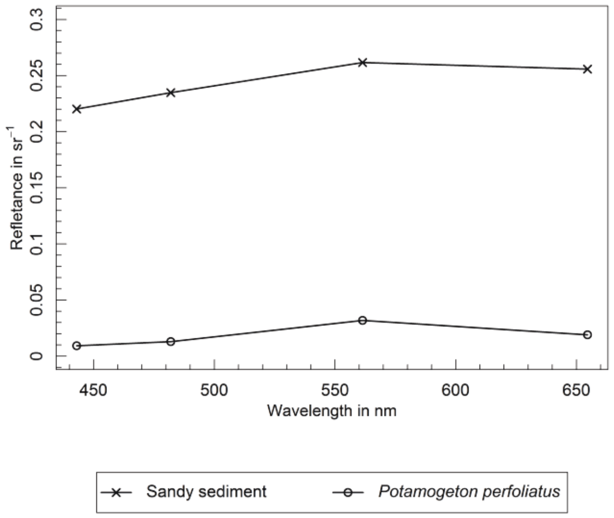

FIG 2. Endmember spectra of sandy sediment and *Potamogeton perfoliatus* resampled to the spectral response curves of Landsat 8.

Further variable parameters were water depth and absorption by CDOM $a_{CDOM(440nm)}$ (TAB 3). Phytoplankton and suspended particulate matter concentrations were constant model parameters (TAB 3). For both, constant and variable parameters, we used the results from laboratory for parameter setting.

3. RESULTS AND DISCUSSION

Applying the deep water model to the entire lake resulted in 1,058 pixels which reached the maximum number of iterations. As mentioned above, we classified these pixels as optically shallow water; they formed a one to two pixel wide band alongshore except in the north, where the shallow water extends up to 300 metres (bathymetry in Fig. 1 and Fig. 2). Modelled water depth was ≤ 2 m while measured Secchi depths ranged between 1.45 and 2.0 m (TAB 1). Thus, the definition of optically shallow pixels seemed to be reasonable.

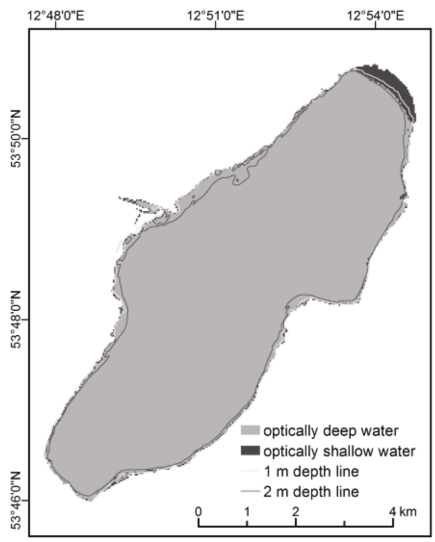

FIG 3. Water pixels classified as optically deep and shallow.

3.1. Optically deep water

The majority of water pixels was optically deep water (33,573 pixels) for which WASI-2D successfully retrieved concentrations of Chl-a, SPM and $a_{CDOM(440nm)}$ (FIG 4). TAB 4 summarises averaged model result.

	Mean	**Median**	**Stdev**	**Min**	**Max**
Chl-a [µgl^{-1}]	0.07	0.03	0.76	0.0	56.62
SPM [mgl^{-1}]	7.21	6.91	1.68	3.58	30.0
$a_{CDOM\ (440\ nm)}$ [m^{-1}]	0.71	0.67	0.13	0.0	1.78
g_{dd} [sr^{-1}]	0.49	0.48	0.13	0.01	1.3

TAB 4. Average results of variable model parameters in optically deep water.

WASI-2D derived lower Chl-a concentrations compared to laboratory results while SPM concentrations were higher. Chl-a showed maximum values in the middle of the lake; highest concentrations of SPM up to 30 mgl^{-1} occurred in shallow water up to 4 m depth which can be explained by wind exposure, sediment inflow by rivers and bank erosion. $a_{CDOM(440nm)}$ which mainly originates from allochthonous sources was low and in a reasonable range for a lake with an agricultural hinterland [24]. The spatial distribution of water constituents resembled streaks following the morphology of the lake which are presumably wind-induced. The modelled SPM concentration was higher than the analysed water sample (TAB 1). However, the model results seemed to be realistic for this type of lake. This points towards an problematic issue when comparing *in situ* water samples and remote sensing measurements; upscaling of the small-scale *in situ* sample to the spatial resolution of remote sensing data is crucial but error-prone [21, 25]. In the case of Landsat 8 water constituent concentrations of a 1 l sample are compared with a remotely sensed concentration valid for 30 x 30 x penetration depth [m]. Laboratory results may therefore merely serve as a rough evaluation of modelling results. Nevertheless, Lake Kummerow is a highly productive lake and was evaluated as eutrophic during the last years [26]. Modelled Chl-a concentrations of 0 µgl^{-1} in large parts of the lake are also unrealistic. Further adapting WASI-2D to lake-specific conditions such as phytoplankton assemblage, diffuse attenuation coefficient and CDOM absorption may improve modelling results. A cyanobacterial bloom observed by MLUV staff in July could further explain errors in modelling because absorption by phycocyanin, the light absorbing pigment of cyanobacteria, is not included in WASI-2D. Moreover, bio-optical modelling is a physically-based approach; fit quality therefore relies strongly on the quality of pre-processing such as an accurate atmospheric correction adapted for inland waters. Hitherto, an operational atmospheric correction for inland waters is not available [27]. Comparisons of atmospherically corrected Landsat 8 and *in situ* measured spectra revealed overcorrection of atmospheric scattering and absorption. Fitting of the parameter g_{dd} (fraction of sky radiance due to direct solar radiation) reduced atmospheric correction errors in the model [11].

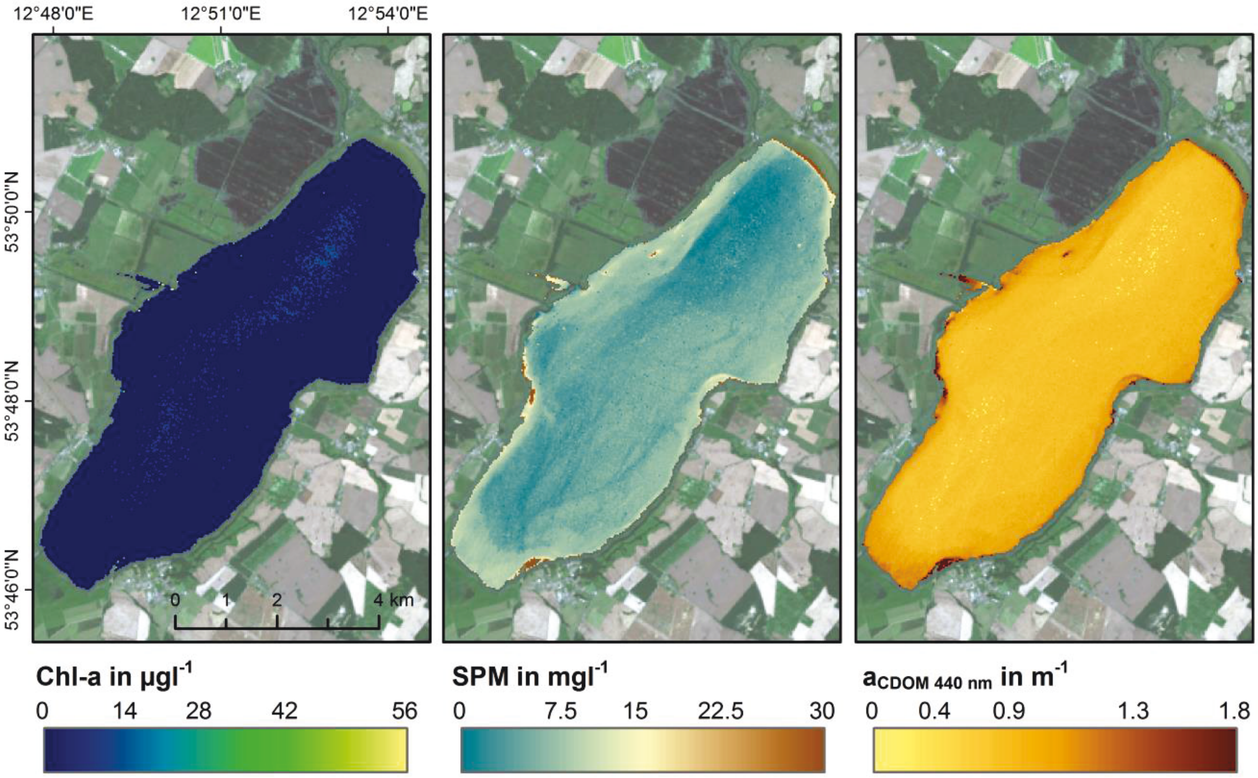

FIG 4. WASI-2D results of Chl-a, SPM and $a_{CDOM\ (440\ nm)}$ of optically deep water.

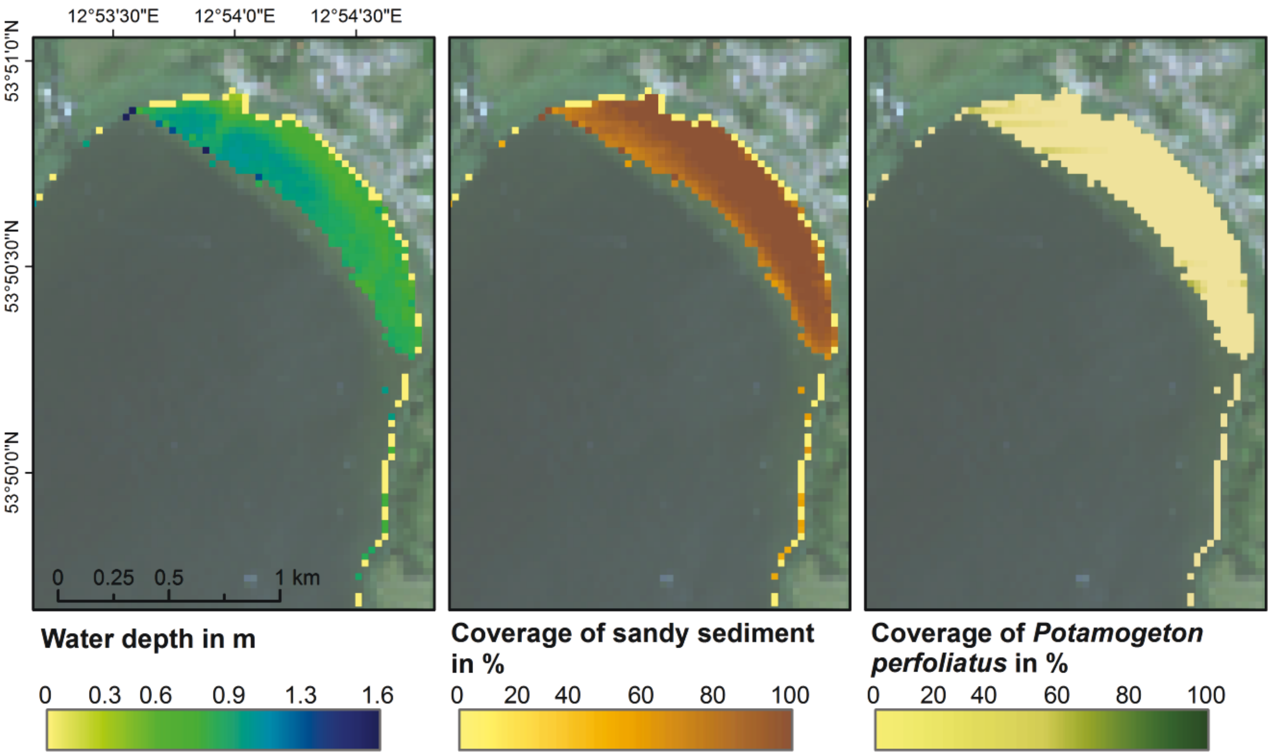

FIG 5. WASI-2D results of water depth, coverage of sandy sediment and *Potamogeton perfoliatus* in optically shallow water.

3.2. Optically shallow water

WASI-2D successfully derived water depths, $a_{CDOM(440nm)}$ and coverages of sandy sediment and *Potamogeton perfoliatus* (cf. Fig. 5). TAB 5 lists average values of WASI-2D modelling results.

	Mean	**Median**	**Stdev**	**Min**	**Max**
Water depth [m]	0.42	0.58	0.35	0.0	1.63
Coverage *Potamogeton perfoliatus* [%]	0.9	< 0.01	4.7	0.0	70.6
Coverage sandy sediment [%]	48.5	50.4	42.3	0.0	100
$a_{CDOM\ (440\ nm)}$ [m^{-1}]	0.71	0.98	0.60	0.0	1.78

TAB 5. Average results of variable model parameters in the optically shallow water parameterisation.

In the northern shallow water area modelled bathymetry slightly increased from the shoreline towards the middle of the lake. The value range between 0.4 and 1.6 m is reasonable. The border between optically shallow and deep water was between the 1 and 2 m bathymetry contour (FIG 3). For methods such as multibeam sonar water depths are too shallow [28]. However, since macrophytes are sensitive to water level changes information on water depth is of great value for lake ecology, especially in the shallow waters [21]. Unmixing the shallow water pixels revealed that sandy sediment dominates while there are only a few pixels with low *Potamogeton perfoliatus* coverage. Unfortunately, the WFD provides for a biennial macrophyte mapping which did not cover the year 2014. Mapping results are therefore unavailable; visual observations in the north of the lake, however, supported the presence of mainly sandy sediment as well as sparse macrophyte vegetation. High SPM concentrations in the shallow water (also visible at the western edge to the shallow water in FIG 4) and backwater effects support sedimentation to the detriment of macrophyte growth. During the field campaign we could observe only small patches (< 30 m²) of *Potamogeton perfoliatus* and *pectinatus*. Owing to the sensor's spatial and spectral resolution we did not distinguish the two macrophyte species for unmixing. Further analyses, however, may include both macrophyte species. To this end, at optically shallow water we rather intend to use satellite data with higher spatial resolution such as RapidEye.

4. CONCLUSIONS AND NEXT STEPS

This study conducted a first feasibility test for deriving indicators of lake ecology using Landsat 8 OLI data and the bio-optical model WASI-2D at Lake Kummerow, Northern Germany. We successfully derived concentrations of Chl-a, SPM and $a_{CDOM\ (440\ nm)}$ in optically deep water. In the optically shallow water, mainly the siltation area in the north, we were able to obtain water depths as well as coverages of sandy sediment and the macrophyte species *Potamogeton perfoliatus* reasonably. Modelled Chl-a concentrations, however, were underestimated in large parts of the lake. Results for the optically shallow water were also reasonable. Despite its spatial resolution of 30x30 m Landsat 8 OLI could illustrate the bathymetric conditions in the shallow area of Lake Kummerow reasonably well. However, we expect that satellite data with higher spatial resolution may resolve more spatial details. A major limitation was the atmospheric correction which entailed uncertainties in water reflectance. Therefore, we will follow up with a detailed analysis of atmospheric correction procedures over water such as the recently published ACOLITE approach [29]. We will further adapt specific optical properties in WASI-2D to better represent characteristics of Lake Kummerow. In addition, ongoing water sampling will provide uncertainty estimates of *in situ* data which we intend to integrate into future studies.

Our results showed that it is worth the effort to adapt bio-optical models for retrieving indicators of lake ecology by means of remote sensing. Weather conditions and discharge affect the lake in its hydrological, chemical and biological composition and induce spatio-temporal heterogeneities of water constituents which *in situ* measurements or mapping are unable to capture. Combing remote sensing and *in situ* measurements will definitely improve lake monitoring and understanding of lake ecology.

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