Bathymetry Estimates and Bottom Classification using Hyperspectral Data in the Baltic Sea

Scientific work to obtain the degree M.Sc. at the Chair of Hydrology and River Basin Management at Technical University Munich.

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Abstract

The water depth of the coastal areas is subject to change due to erosion and sediment accumulation processes and the effects of the sea level rise. Knowing the accurate water depth is not only essential for scientific research and the shipping industry but also for water authorities and decision makers. Remote sensing derived bathymetry can fill the data gaps with better coverage than conventional methods. Especially physical based methods allow for the estimation of water depth, in addition to water constituents and the bottom cover.

This master thesis focuses on the determination of the bathymetry and bottom cover of coastal areas in the German Baltic Sea by inverting airborne hyperspectral imagery (HySpex VNIR-1600) and simulated EnMAP data with a semi-analytical inversion program based on a radiative-transfer model. Furthermore, the expected accuracy of the water depth retrieval and the bottom classification was quantified based on simultaneously acquired in situ sonar measurements and a customized spectral database of the bottom cover types in the study area.

The validation of the retrieved water depths was conducted for three sites which vary in their bottom cover types and exhibit different water depth distributions. The first (1) and second (2) site yield water depth estimates for the HySpex imagery with (1): up to +/- 15 % mean systematic error for water depths up to 6 m when calculating the mean water depth difference with a 50 cm binning interval and with (2): up to +/- 25 % systematic error for water depths up to 10 m. The corresponding Mean Absolute Percentage Error MAPE were derived with (1): 14 % and (2): 19 % for water depths smaller than the averaged Secchi depth of 5.7 m. The inversion of HySpex image covering the third (3) site failed probably due to the dark bottom cover. The corresponding errors of the water depths were (3): up to + 240 % for the mean error and 192 % MAPE for water depths up to 7 m, and Secchi depth respectively.

The bathymetry results for the EnMAP simulated scene were evaluated for the same sites: site (1) yields systematic errors up to +/- 18 % for binning intervals of 1 m up to 6 m water depth. Site (2) exhibits a mean systematic water depth error from - 45 % to 0 % up to 10 m water depth. The mean systematic error for the third site (3) is in order of + 120% for water depths up to 7 m. The corresponding MAPE for water depths up to the averaged Secchi depth are (1): 13 %, (2): 15% and (3): 100 %.

The bottom classification using HySpex and simulated EnMAP imagery could not be validated since independent measurements were not available. The comparison with true-colour images derived from HySpex yielded plausible results for sand in all study sites up to the Secchi depth. Other bottom covers including sea grass and mussels were used during the inversion but could not be verified since these could not be distinguished in the true-colour images.

To conclude, the bathymetry estimates and bottom classification determined in the scope of this master thesis showed convenient results for water depth over shallow and bright areas but not over dark areas. The results for the EnMAP simulated scene displayed similar accuracies as for the HySpex imagery.
Acknowledgements

First, I would like to thank my supervisor at DLR, Dr Peter Gege, for his constant support during all stages of this master thesis, especially for all the time he took to discuss the encountered difficulties.

I would also like to thank my university supervisor, Dr Zheng Duan, for his support and his confidence in me during the Master course.

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Last, I want to thank my parents and my big sister for believing in me and supporting me all the time.
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1 Introduction

The water depth of the coastal areas is subject to change due to erosion and sediment accumulation processes driven by water currents and river estuaries. Additionally, the temperature of the ocean waters increases due to impacts of climate change, with an average rate of 0.11°C per decade measured in the upper layer up to 75 m water depth and over the period from 1971 to 2010 [BMU et al., 2017]. Together with the melting of glaciers and ice shields this contributes to an averaged sea level rise of 3.2 mm per year measured over the last 20 years. The prognosis of the International Panel on Climate Change suggest a sea level rise of 26 to 55 cm until the end of the 21st century as a best case scenario, the worst case scenario assumes a rise from 45 to 82 cm [BMU et al., 2017]. The combined effects result in temporal and spatial highly variable water depths along the coast lines. Knowing the accurate water depth is not only essential for scientific research and the shipping industry but also for water authorities and decision makers as it provides valuable information for water resource management and hydraulic engineering interventions.

Conventional methods for water depth detection include the single/multibeam sonar from ship and the airborne Light Detection and Ranging (Lidar). Both methods provide high depth accuracy on centimetre-level, but are expensive and time-consuming when applied to larger areas [Mohamed et al., 2017; Hodúl et al., 2018]. The ship-based echosounder technique is also limited in very shallow regions (less than 4 m), depending on the ship’s draught [Hodúl et al., 2018; Pacheco et al., 2015].

Remote sensing derived bathymetry provides better coverage than the conventional methods and especially satellite based imagery can assure regular data acquisition which enables change detection and easy, cost-efficient access. Many remote sensing methods are based on optical imagery, particular on multi-spectral [Jagalingam et al., 2015; Mohamed et al., 2016; Adler-Golden et al., 2005; Hodúl et al., 2018; Stumpf et al., 2003] or hyperspectral imagery [Jay and Guillaume, 2014; Brando et al., 2009; Ma et al., 2014; Dekker et al., 2011].

The methodology to derive the water depth, information about water constituents and benthos from optical imagery can be roughly categorized into empirical and semi-analytical methods. The physical principle is thereby exploited: incoming sun light is absorbed, scattered and diffused in the water column by the water molecules and water constituents and partly reflected at the bottom. The signal leaving the water body is thereby dependent on the water depth [Jawak and Luis, 2014]. Comparing the received signals of multiple bands allows for the estimation of the water depth (e.i. the thickness of the water column) and with more complex methods for the estimation of the water constituents and bottom type, as the absorption, scattering and reflection processes are dependent on the wavelength.

This master thesis is embedded into the project CoastMap, evaluating the potential of the satellite mission EnMAP [Guanter et al., 2016] for bathymetry determination and bottom classification using a semi-analytical method, where the physical processes of the light travelling through the water column are modelled. CoastMap was commissioned by the Centre for Geoinformation of the German Armed Forces (ZGeoBW) and carried out by the German Aerospace Center (DLR) and the Fraunhofer Institut of Optronics, System technology and Image analysis (IOSB).

The scope of this master thesis is to derive water depth and bottom cover maps from airborne hyperspectral images and EnMAP-simulated hyperspectral data with a semi-analytical inversion program. Therefore, various sensitivity analysis are conducted to find the relevant fit parameters for the bottom types, the water constituents and surface effects. Different combinations of fit parameters are tested on small image subsets
to verify the results of the sensitivity analysis and evaluate the inversion stability. The selection of best fit parameters is applied to three regions which are characterised by different depth distribution and bottom cover composition. Last, the inverted water depths are validated using sonar measurements. The data basis was acquired during a preceding campaign at the German Baltic Sea in 2016. Additionally, the expected accuracy and possible limitations for both water depth and bottom cover determination will be evaluated and the best strategy to derive stable and reliable inversion results will be documented.

The second chapter gives a short introduction to the state of the art of empirical, physical and other approaches to derive water depth from optical remote sensing data. The third chapter describes the study area, the used remote sensing and in situ data and summarises the pre-processing steps. The semi-analytical inversion program is described in section 3.3. The fourth chapter summarises the results for the bathymetry and bottom cover maps as well as the best inversion approach. The results are discussed in the fifth chapter and an outlook is presented in the sixth chapter. Last, the findings of this master thesis are summarised in chapter seven.
This chapter provides an overview of the state of the art of remote sensing bathymetry estimation, in particular focusing on the empirical and physical approaches to derive the water depth and bottom cover from hyperspectral imagery. Table 2.1 summarises relevant studies deriving the bathymetry and additional water information. The table is organised in three parts: the first part focuses on studies which derived the water depth with physical methods. The next part summarises studies which applied empirical methods and the last part includes studies which applied approaches other than physical or empirical based.

Brando et al. [2009], Adler-Golden et al. [2005] and Dekker et al. [2011] were able to derive the water depth with a RMSE ranging from 0.67 m to 2.36 m and bottom cover types by applying a physical inversion algorithm to hyperspectral imagery. Dekker et al. [2011] compared 6 different empirical and physical approaches for two study sites - the two best methods were physical based and yielded a RMSE of 0.91 and 0.94 m. The later result was derived with the adapted method of [Brando et al., 2009]. The limitation for reliable water depth retrieval was found to be in range from 7 to 13 m water depth. Adler-Golden et al. [2005] yielded an RMSE of circa 1 m for both hyperspectral and multispectral imagery and the water depth retrieval was possible for water depths up to 10 m. The results of these studies provide a baseline for the expected RMSE of the water depth retrieval and the water depth limit for a physical inversion approach.

Empirical methods derive the water depth by establishing a relationship of the water leaving signal with known water depths. The water constituents are hereby assumed to be constant over the area of interest. Jagalingam et al. [2015], Stumpf et al. [2003] and Ma et al. [2014] derived the water depth successfully by applying an empirical relationship to the signal of blue and green bands for water depths up to 30 meters. The RMSE of water depth derived by Ma et al. [2014] ranges from 0.84 m to 1.87 m.

The last part includes the photogrammetric extraction method by Hodúl et al. [2018], who derived the water depth with an RMSE of circa 1.2 m. Mohamed et al. [2016] applied a new machine learning method to Spot-4 imagery and determined the water depth of the shallow study area with a maximum depth of 2 m with an RMSE of 15 cm. Jay and Guillaume [2014] utilised a maximum likelihood function which derived the water depth up to 14 m with an RMSE of 0.54 m.
<table>
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<tr>
<th>Study</th>
<th>Data/model used</th>
<th>Key results</th>
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<tr>
<td>Brando et al. [2009]</td>
<td>• Cloud contaminated airborne hyperspectral images over Moreton Bay, Australia; Multi-beam acoustic water depth measurements ranging from 4 to 13 m; Bottom cover spectra for sand and mud; water analysis; • Physical inversion approach based on Lee et al. [1999] including quality control procedure to identify cloud &amp; shadow free pixels to derive: bathymetry, bottom cover &amp; water constituents; • Quality assessment by calculating similarity of modelled below-surface reflectance and image reflectance (optical closure, optimization residuum) while estimating the contribution of bottom cover signal (substratum detectability index SDI) to reflectance signal in order to classify optical shallow waters;</td>
<td>• Class definition by SDI: optically shallow &amp; good closure (SDI&gt; 15, RMSE: 0.67 m), optically shallow &amp; bad closure (cloud exposed) and optically deep pixel with good &amp; bad closure (1&lt;SDI&lt;5, RMSE: 1.35 m) • Depth precision: function of SDI; Accuracy: function of model calibration &amp; atmospheric corrections</td>
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<td>Adler-Golden et al. [2005]</td>
<td>• QuickBird satellite imagery, Littoral Airborne Sensor: Hyperspectral (LASH), Airborne Visible/Infrared Spectrometer (AVIRIS) imagery over Kaneohe Bay and Tampa Bay, US; ground-truth bathymetry data; • Bathymetry method assuming constant water constituents including atmospheric correction using modified MODTRAN &amp; FLAASH, water reflectance simulation &amp; linear unmixing bathymetry algorithm;</td>
<td>• Depth retrieval in 0-10 m range agrees with Literature (LASH: mean system error -25%, QuickBird:average error ca. 1 m, AVIRIS: average error ca. 1 m) • Overall satisfactory removal of glint effects of order 0.1 reflectance &amp; improved aerosol characteristics</td>
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<tr>
<th>Study</th>
<th>Data/model used</th>
<th>Key results</th>
</tr>
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</table>
| Dekker et al. [2011] | • Quality comparison of five radiative-transfer methods and one empirical method to derive water depth, water constituents and bottom from hyperspectral imagery (Ocean PHILIPS & CASI-2) cover over optically shallow regions at the coast of Lee Stocking Island, Bahamas & Moreton Bay, Australia.  
  • Methods:  
  M1. band-ratio algorithm by Lyzenga  
  M2. HOPE: Hyperspectral optimization process exemplar model (by Lee et al., 1999; Binary bottom cover)  
  M3. BRUCE: Bottom reflectance un-mixing computation of the environment model (by Lee et al. [1999]; Linear combination of 3 bottom spectra)  
  M4. SAMBUCA: Semi-analytical model for bathymetry, un-mixing, and concentration assessment (by Lee et al. [1999]; Retrieval of water constituents; 2 bottom spectra & contribution of bottom to signal with SDI [see Brando et al. [2009]])  
  M5. CRISTAL: Comprehensive reflectance inversion based on spectrum matching and table lookup (by Mobley et al., 2005; & matching with precalculated Hydrolight database)  
  M6. ALLUT: Model inversion by adaptive linearised look-up trees (by Hedley et al., 2009; Matching with spectral look-up tree based on parameter space which is subdivided to represent an evenly sampled spectral space; LUT spectra created with forward mode of HOPE, SAMBUCA)  
  • sea grass cover maps with ENVI Spectral Angle Mapper using retrieved bottom reflectances from Models 2.-6. | • Bathymetry accuracy: M1 < LUT-based (M5, M6) & M2 < SA-based (M3, M4)  
  • Depth limitation: 7-13 m; RMSE (Lee Stocking Island):0.91 (M3) - 2.36 m (M6), RMSE (Moreton Bay): 0.96 (M4) - 4.71 m (M5)  
  • No universal method, but relevant environmental conditions detectable by M2-M6; Image quality partly affecting accuracy negatively;  
  • Water constituents values most accurate over optically deep water  
  • Low bottom accuracy for mixed/small bottom cover  
  • M3, M5, M6 may produce better bottom cover maps but not if wrong bottom cover types are chosen during LUT-design; |
| Ma et al. [2014] | • Hyperspectral Hyperion imagery (30 m resolution) of coast of O’Ahu Island & Saint Thomas Island; LIDAR water depth;  
  • Algorithm for shallow water (0-30 m) detection based on [Stumpf et al., 2003], depending on spectral responses of benthic and water depth changes. Evaluation of spectral signals (<0.15 m for reference) in range from 480-610 nm with Pearson correlation coefficient (CC), similarity coefficient (SC); | • RSME for total water depths between 0.84 and 1.87 m; Consistent results for different areas for <= 20 m but underestimation for water deeper than 20 m;  
  • Method by Stumpf et al. [2003] lower accuracy in 0-5 m water depth because only two bands used for calibration of model, which are sensitive to bottom cover;  
  • Limitation: Assumption of uniform water constituents; |
| Jagalingam et al. [2015] | • Landsat-8 imagery of southwest coast of India; hydrographic charts derived from sonar measurements;  
  • Retrieval of water depth with ratio transform algorithm by Stumpf et al. [2003]; | • $R^2 = 0.8781$  
  • Limitation: Hydrographic chart resolution with 0.1 m, training data not explained; |
### Table 2.1: Overview of selected bathymetry methods using aerial or satellite imagery.

<table>
<thead>
<tr>
<th>Study</th>
<th>Data/model used</th>
<th>Key results</th>
</tr>
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| Stumpf et al. [2003]          | • IKONOS satellite imagery over coral reef atolls in Hawaiian Islands; reference Lidar bathymetry & Nautical charts;  
                                 | • Empirical ratio algorithm to derive bathymetry $z$ in clear waters with variable benthic & bottom cover;  
                                 | $z = m_1 \ln(n R_{\text{w}}(\lambda_i)) - m_0$ (2.1) 
                                 | with $n$ being a (negative) constant to force positive logarithm values, $m_1$ being the scaling factor, $m_0$ the offset for zero depth and $R_{\text{w}}$ the reflectance values of the channels blue and green $i, j$; $m_0, m_1$ were adjusted to match depths of nautical charts;  
                                 | • Depth and spatial features match Lidar results for shallow and low turbid waters $0.6 \text{ m} < z < 30 \text{ m}$;  
                                 | • normalised RMSE = 0.3 for $z < 25 \text{ m}$  
                                 | • Limitation: Not applicable where shallow water reflectance values are smaller than in deeper waters;  
| Mohamed et al. [2016]         | • Spot-4 satellite imagery over EL-Burullus Lake, Egypt; Echo sounder water depth;  
                                 | • Comparison of new Ensemble Learning (EL) fitting algorithm of Least Squares Boosting (LSB) with Principal Component Analysis (PCA) and Generalized Linear Model (GLM);  
                                 | • Input for algorithms: log (green) and log (red);  
                                 | $R^2_{\text{PCA}} = 0.479 < R^2_{\text{GLM}} = 0.527 < R^2_{\text{LSB}} = 0.618$  
                                 | • $RMSE_{\text{PCA}} = 0.19 \text{ m} < RMSE_{\text{GLM}} = 0.18 \text{ m} < RMSE_{\text{LSB}} = 0.15 \text{ m}$  
                                 | • Limitation: Method tested over very shallow region ($\leq 2 \text{ m}$);  
| Hodúl et al. [2018]           | • WorldView-2 stero pair over Coral Harbour, Canada; Hydrographic survey data;  
                                 | • Bathymetry extraction by photogrammetric extraction based on feature extraction (water line elevation) and image geometry (under-water points), including noise and blunder removal & refraction correction term;  
                                 | • Mean water depth error: 0.031 m  
                                 | • RMSE: 1.178 m  
                                 | • Limitation: applied under wave-free, clear water conditions;  
| Jay and Guilhoume [2014]       | • Hyperspectral images with Hyspex VNIR-1600 camera (0.4 to 2 m spatial resolution) at French west coast; Library of bottom spectra; Water analyses;  
                                 | • Statistical mapping method using: surrounding pixels combining pixel-based (derived over 0.5 x 0.5 $m^2$) linear depth estimates inserted in a maximum likelihood (ML) function for shallow water regions ($< 10 \text{ m}$) with standard ML mean water depth estimates (derived over 8x8 $m^2$) for deep water regions ($> 10 \text{ m}$);  
                                 | Estimation of water column properties based on linear and constant water depth model;  
                                 | • Linear depth model beneficial for depth & water constituent estimates over shallow regions in comparison to standard ML estimate;  
                                 | • RMSE: 0.54 m  
                                 | • Limitation: Bottom cover modelled with single sand spectrum;  
                                 | Water depth retrieval limited to $\leq 14 \text{ m}$;  
| **Table 2.1:** Overview of selected bathymetry methods using aerial or satellite imagery.
3 Materials and methods

3.1 Study area

The field campaign took place at the Baltic sea, at the coast north of Wismar, Germany, during April 11-21, 2016. The 14 km x 14 km large area is characterized by shallow coast lines in the western and southern part (Boltenhagen, Wohlenberg) and vegetated areas to the East (Poel). The water near the coastline is known to be shallow with depths normally below 15 m. The campaign was conducted during a time frame where relatively few aquatic plants were expected due to the reduced growth during winter and based on the results of a preceding bachelor thesis evaluating the Secchi depths in the study area over a time frame from 2008 to 2012 [Auer et al., 2016; Hübner, 2014]. The absence of aquatic plants is favourable for optical remote sensing as the water is supposed to be clear.

3.2 Data

The following section describes the acquisition and correction of the HySpex imagery for better comprehension. The data utilized in this master thesis was already provided in the preprocessed format, however the following overview provides the basis for understanding any data limitations that may occur. Figure 3.1 summarises the preprocessing steps in blue and the tasks conducted in the course of this master thesis in green.

![Flow chart of preprocessing steps](image)

Figure 3.1: The flow chart displays the preprocessing steps applied prior to this master thesis in blue and the tasks performed in the scope of this master thesis in green.

3.2.1 HySpex imagery

3.2.1.1 Data set

The hyperspectral images were obtained by passive remote sensing, using the two air-borne pushbroom sensors Norsk Elektro Optikk (NEO) HySpex VNIR-1600 and SWIR-320m-e. The pushbroom sensor enables the quasi-simultaneous detection of the incoming signals from one scan line.

The working principle of the pushbroom sensor is illustrated in Figure 3.2. Each signal coming from one pixel of the scan line is spectrally decomposed and mapped onto the detector. The spectral composition
yields quasi-monochromatic beams which are mapped in z-direction on the corresponding channel. Mapping the light of every line scanner pixel onto the detector results in an array defined by the number of spatial pixels in y-direction and spectral channels in z-direction.

In the following, the VNIR-1600 instrument will be denoted as VNIR-sensor and the SWIR-320m-e as SWIR-sensor. The combination of both sensors enables the spectral range from 416 nm to 2497 nm with a small overlap between 968 nm and 992 nm where both sensors can detect signals. The VNIR-sensor detects signals in the visible to near infra-red wavelength (VNIR) every 3.6 nm (channel width), at a spectral resolution of circa 3.5 nm. The SWIR-sensor detects signals in the short wavelength infra-red (SWIR) with a sampling interval of 6 nm. Both sensors were equipped with a field-of-view expander lens to increase the spatial coverage of one flight line. The resulting field of view was 34.5° for the VNIR-sensor and 27.2° for the SWIR-sensor, respectively [Lenhard et al., 2015]. The images from the different flight lines were combined to a mosaic. The flight height of the aircraft determines the ground resolution. Two flight heights were chosen to provide a 1 m x 1 m pixel size (flight height ca. 650 m) and a 4 m x 4 m resolution (flight height ca. 2600 m). The flight lines overlapped partly and therefore, the mosaic can exhibit different properties depending on which flight line is chosen during the mosaicking process for the overlapping space. Three areas (Zone 1, Zone 2 and Zone 3, see Figure 3.3) covering coast, shallow water and deep water regions were defined and extracted from the mosaic. These areas incorporate the regions where sonar measurements were conducted and are the basis for this master thesis.

The selected scenes display not only various bottom type compositions but exhibit also different water depth distribution, as can be seen in Figure 3.4.

3.2.1.2 Sensor characterisation

A brief introduction to the applied characterization and calibration steps is summarized in the following section. All pre-processing steps were conducted prior to this master thesis by DLR.

Both sensors were characterized in the DLR Calibration Home Base [Baumgartner et al., 2012] in 2016 to provide the necessary information for the sensors calibration [Auer et al., 2016; Lenhard et al., 2015]. Three different measurement set-ups were used to characterize every detector element: radiometric, spectral and geometric measurement.

The sensitivity of each detector element towards a uniform light field was characterized during the radiometric measurement and defines the radiometric response $R_{i,j}$ of the detector elements. The radiance of the light source can be traced to SI units via a calibrated spectral radiance standard. Since only the centre pixels of the HySpex sensor could be measured with the standardised light source due to geometry constraints, the characterisation of the remaining pixels requires a subsequent measurement where all pixels are illuminated by a light source which illuminates the instantaneous field of view homogeneously.

For the spectral measurement, the wavelength of the illumination source was varied using a monochromator and individual pixels were illuminated with the different wavelengths to retrieve the wavelength-dependent relative intensity. The resulting curve displaying the relative intensity against the illumination wavelength is called the spectral response function (SRF). It can be well approximated with a Gaussian
3.2. DATA

Figure 3.3: Selected test areas from the HySpex mosaic: The blue lines indicate the locations of the sonar measurements, the green-white and black-blue dots the measuring positions of the two ships.

function. The characteristics of the function are the centre wavelength at which the maximum intensity is detected and the width of the curve at the half of the maximum (Full Width at Half Maximum, FWHM). A subsequent fit of all SRFs measured at different pixels is applied to interpolate the spectral properties for all pixels. The 'Smile' distortion describes the difference of the centre wavelength of one detector element to the centre wavelength measured at the centre detector element of the sensor.

The geometric measurement was conducted with a white light beam which was directed towards the detector elements with a moveable mirror. The relative intensity measured at one detector element by varying inclination angles of the light beam resembles a Gaussian curve and is called line spread function (LSF). Both along- and across-track LSFs are measured. They are characterized by a maximum at the centre angle and the width measured at half of the maximum relative intensity, denoted as the angular resolution. The along-track centre angles and the angular resolutions are fitted with a second-order polynomial, for the across-track direction with an fourth-order polynomial. The position of the intensity maximum changes with spectral bands for the same detector column, where the maximum difference of viewing angles in across-track is denoted as the ’keystone’ distortion.

3.2.1.3 Radiometric and spectral calibration

First, the results of the radiometric measurements were used to calibrate the detector elements to at-sensor radiance as follows:

\[ L_{i,j} = \frac{S_{i,j} - S_{i,j}^{ds}}{R_{i,j} \cdot t_{int}}, \]  

with \( L_{i,j} \) denoting the at-sensor radiance in \( \frac{mW}{m^2 \cdot nm \cdot sr} \), \( S_{i,j} \) the measured signal in digital numbers DN, \( S_{i,j}^{ds} \) the dark signal, composed of electric offset and thermal dark current, in digital numbers DN, \( R_{i,j} \) the radiometric response in \( \frac{m^2 \cdot nm \cdot sr \cdot DN}{\mu s \cdot mW} \) and \( t_{int} \) the integration time in \( \mu s \). The dark signal is measured by taking 200 frames with a closed shutter, which is done automatically before the acquisition. The averaged frame can then be used to remove the dark signal.

Secondly, the signals of the bad detector elements were removed, based on the bad pixel map provided
CHAPTER 3. MATERIALS AND METHODS

by the manufacturer of the camera. The removed signals were linearly interpolated for every band.

Last, the optical distortions Keystone and Smile were corrected based on the results of the geometric and spectral characterisation. Both distortions were corrected at the same time by applying a bicubic spline interpolation using the Keystone and Smile maps. The image is now in units of at-sensor radiance. [Lenhard et al., 2015].

3.2.1.4 Geometric correction and image rectification

Accurate geo-referencing is important for a variety of analyses, especially for change detection and mapping [Muller et al., 2002]. The ortho-rectification was conducted with the DLR software ORTHO. The built-in angle of the sensors (interior orientation) was determined by analysing the images acquired over a test area. The interior orientation is defined by the three Euler angles: $\kappa(z), \phi(y)$ and $\omega(x)$. The angles were derived by comparing the test image with a well defined ortho-image and digital elevation model of the test area. The automatic detection of corresponding image points in the HySpex image and the reference ortho-image was conducted with the BRISK (binary robust invariant scalable keypoints) Operator. The exterior orientation of the HySpex images acquired over the German Baltic Sea was derived based on GPS data and a UTM zone 32 map projection.

The combination of internal and exterior orientation enables the ortho-rectification of the HySpex imagery. The overlap of both sensors in the short wave infra-red was used to co-register the SWIR-sensor images to the already ortho-rectified VNIR-images [Auer et al., 2016].

3.2.1.5 Atmospheric correction

The atmospheric correction was applied to co-registered VNIR and SWIR bands, choosing the best fit parameter for each flight line. The same correction parameters were also used for land-areas in the scope of the project, which resulted in a compromise during the correction process. In the following, the chosen correction parameters will be briefly explained. For more detailed description, please refer to the Atmospheric/Topographic Correction for Airborne Imagery (ATCOR) manual [Remote Sensing Software for Image Data Processing, 2018].

The ATCOR module was started using the flat terrain option. The HySpex flight lines were then masked for different pixel types before the atmospheric corrections were applied: haze, cloud, snow, water and clear pixels. This pre-classification was based on at sensor reflectance thresholds [Remote Sensing Software for Image Data Processing, 2018]. The de-shadowing, haze, cirrus or sun glint removal was not applied. The adjacency effects were set to a range from circa 0.1 km for all flight lines or the number of adjacency zones was set to 1. Additionally, the following reflectance thresholds were defined: 25% for clouds, 5% for water pixels in the NIR region, 3% for water pixels in the 1600 nm region and 150% as the maximum surface reflectance threshold.

The dark dense vegetation (DDV) method was applied to derive the visibility for standard atmospheric conditions. It checks if pixels in the 660 nm band (vegetation) and 850 nm band (water) resume negative reflectance values for a chosen visibility. For most flight lines 25 km was chosen as input value. The final visibility lies between 70 km and 100 km and is assumed to be constant for the each flight line, but may differ from one flight line to the other.

The aerosol type, the water vapour and the visibility are the most important atmospheric parameters because they are highly variable in space and time [Remote Sensing Software for Image Data Processing, 2018, page 21]. Especially the aerosol type and load determination are critical for the retrieval of accurate reflectance spectra [Gilerson et al., 2018]. Since the correction was applied over both land and water surfaces, the rural aerosol type was chosen in general. The atmospheric file was chosen according to the corresponding input water vapour. ATCOR adjusts the file automatically for the acquisition geometry (altitude, solar angles).

The water vapour was derived with the atmospheric pre-corrected differential absorption (APDA) algorithm over land pixels, where a box size of 50 m or 13 pixels was chosen. Three bands were used to derive
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the APDA ratio based on at-sensor radiance, path radiance and surface reflectance. In this case, channels from 187 to 191 where chosen as measurement band which corresponds to a wavelength of 1.1237 \( \mu m \) to 1.1476 \( \mu m \). The remaining two bands were situated in neighbouring regions (channel 181 and 207) and were assigned as reference. In order to bypass the necessity of surface reflectance values, the APDA ratio for the absorption band can be expressed in terms of atmospheric transmittance \( \tau \) and global flux \( E_g \):

\[
R_{APDA}(u) = \frac{\tau(u)E_g(u)}{\tau(u=0)E_g(u=0)} = exp(-\alpha + \beta \sqrt{u}), \tag{3.2}
\]

where \( u \) is the water vapour column. The equations are solved iteratively by starting with a water vapour column value, deriving the APDA ratio and then updating the variables \( u \), the path radiance and the surface reflectance values. The average of the land water vapour mask was also used for the water pixels. The derived values were in the range from 0.75 cm.

To retrieve information from dark surfaces like the ocean, the radiometric gain is adjusted which may lead to saturation of bright targets. For that reason, a mask highlights the saturated land pixels. Since this master thesis focuses on the data covering the water region only, the mask is not used.

3.2.2 In-situ data

3.2.2.1 Sonar measurements

The sonar measurement were conducted by the Limnological Institute of the Technical University Munich (TUM) on an inflatable boat at three coastal areas. The sonar equipment is manufactured by LOWRANCE and part of the HDS-8/HDS-10 Fish Finding Sonar and GPS series [Navico Holding AS, 2008]. The instruments allow for sonar imaging through the StructureScan™ technology: the dual-frequency sonar measures downward as well as sideways [Navico Holding AS, 2009]. A suitable depth/temperature transducer is combined with the sonar to derive depth and temperature values (the used transducer is out of the market, specifications of the used device can be found at [Navico Holding AS, 2016]). The measurement data was provided as comma separated text-file and includes the coordinates in DHDN (German Main Triangulation Network) Zone 4, the latitude and longitude, the measured depth in meter and three coefficients which are connected to the bottom composition (hardness and roughness) and were derived with the commercial software ReefMaster [ReefMaster Software Ltd., 2017]. The coordinates were converted to the UTM 32 N coordinate system which is also used for the HySpex images. The conversion was conducted with an open source excel sheet [GeoGeek, 2018]. In the master thesis of Stolz [2017], the agreement of the sonar water depths with the water depth charts from the Federal Maritime and Hydrographic Agency (Bundesamt für Seeschifffahrt und Hydrographie) was derived. The results showed that the sonar water depths diverged with a maximum relative error of 2.7 %, corresponding to a maximum absolute error of 21 cm. Consequently, the measured sonar water depths can be used as the ground reference with confidence. The resulting depth distribution for the three HySpex zones is displayed in Figure 3.4.

3.2.2.2 Spectral database and water constituents

The inversion process requires prior knowledge of spectral properties of the sea bottom and water constituents. A spectral database classifying the different bottom cover types of the study area based on the corresponding irradiance reflectance was derived by Schnalzger [2016] in her master thesis. The different bottom cover types consist of mussels, sea grass, red and brown algae, sand, clay and loam. Two different average spectra were derived for each bottom type based on the spectral properties, except for clay. The corresponding spectra are listed in Table 3.1.

Additionally, water samples were analysed for the total suspended matter concentrations (TSM), the concentration of chlorophyll-a, the absorption coefficient of coloured dissolved organic matter (CDOM) at 440 nm \( a_{CDOM} \) and the spectral slope of COM absorption \( S_{CDOM} \). The averaged values as listed in Table 3.2 are used as start values during the inversion process.
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Figure 3.4: The box plots display the stochastic distribution of measured water depths in the corresponding zones. The box indicates the first $Q_1$ and third quantile $Q_3$, the median corresponds to the second quantile. The whiskers are displayed according to $Q_3 + 1.5 \cdot (Q_3 - Q_1)$ and $Q_1 - 1.5 \cdot (Q_3 - Q_1)$.

<table>
<thead>
<tr>
<th>Bottom type</th>
<th>Sea grass</th>
<th>Mussels</th>
<th>Algae</th>
<th>Sand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Irradiance spectrum</td>
<td>6, 7</td>
<td>4, 5</td>
<td>brown algae, red algae</td>
<td>1, 2, 3, 8, 9</td>
</tr>
</tbody>
</table>

Table 3.1: The spectral database consists of 11 reflectance spectra. A selection of 9 reflectance spectra provides the basis for the bottom classification. The numbers correspond to the spectra displayed in Figure 4.1.
### Table 3.2: Average values of the in-situ measurements of the water constituents: total suspended matter (TSM), chlorophyll-a (Chl), absorption coefficient a and slope S of the concentration of dissolved organic matter (CDOM).

<table>
<thead>
<tr>
<th>Water Constituent</th>
<th>TSM [mg/l]</th>
<th>Chl [µg/l]</th>
<th>a CDOM [1/m]</th>
<th>S CDOM [1/nm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimal value</td>
<td>0.212</td>
<td>0.85</td>
<td>0.2244</td>
<td>0.01797</td>
</tr>
<tr>
<td>Mean value</td>
<td>0.477</td>
<td>1.42</td>
<td>0.2461</td>
<td>0.01831</td>
</tr>
<tr>
<td>Maximal value</td>
<td>0.655</td>
<td>2.08</td>
<td>0.2710</td>
<td>0.01855</td>
</tr>
</tbody>
</table>

The Secchi water depth is of further interest as it estimates the water transparency, which is linked to TSM, CDOM and chlorophyll concentration [Alikas and Kratzer, 2017]. It was measured with the Secchi disk, which was lowered into the water until the bright surface of the disk was just visible to the human eye. The corresponding water depth can be read off the adjusted measuring band. The Secchi depth was measured throughout the areas corresponding to the HySpex zones 1 and 2, with an average value of 5.7 m and a standard deviation of 1 m.

### 3.2.3 Simulated EnMAP data

The HySpex imagery was used in combination of a DEM model to simulate the image properties of the hyperspectral sensors mounted on the Environmental Monitoring and Analysis Program (EnMAP) satellite. EnMAP should contribute to modelling and measuring the key dynamic processes of the ecosystem on global scale, especially for coupled processes [Guanter et al., 2016].

The simulation was conducted by GFZ (German Research Centre for Geosciences) Segl et al. [2012].

The atmospherically corrected HySpex imagery of the entire study site was forward simulated to generate approximated EnMAP raw data. The HySpex surface reflectance values were therefore converted to top of atmosphere radiance values in the atmospheric module, depending on aerosol optical thickness and water vapour as well as surface elevation. The spatial module allows for different spatial recording geometries based on the modulation transfer function of the sensor and the choice of optics. The HySpex signal was spectrally re-sampled to fit the number of EnMAP bands and spectral distortions were added to the spectral response. The last module converts the at-sensor radiance values to digital numbers, including raw data associated noise signals. Afterwards, the raw data was backward simulated including calibration, co-registration, atmospheric correction and ortho-rectification to provide a L2 image of the study site in ENVI-format [Segl et al., 2012].

### 3.3 Algorithm and Software

#### 3.3.1 Analytical model

The analytical model is based on the radiative transfer equation and describes the absorption, scattering and attenuation processes which have an effect on the sunlight passing through the water column as well as processes which occur at the boundary between atmosphere and water.

The ratio of the upwelling radiance at the bottom of the atmosphere (BOA) \( L_u \left[ \frac{W}{m^2 \cdot sr \cdot nm} \right] \), to the downwelling irradiance \( E_d \left[ \frac{W}{m^2 \cdot nm} \right] \), is called the remote sensing reflectance \( R_{rs} \):

\[
R_{rs}(\lambda) = \frac{L_u(\lambda)}{E_d(\lambda)} [sr^{-1}].
\]  

(3.3)

The application of atmospheric corrections to the top of atmosphere radiance yields the BOA radiance.

The remote sensing reflectance above the water surface, \( R_{rs}(\lambda) \) is related to that below the surface, \( R_{sh}(\lambda) \), as follows:

\[
R_{rs}(\lambda) = \frac{(1 - \sigma)(1 - \sigma_L)}{n_w^2} \cdot \frac{R_{rs}(\lambda)}{1 - \rho_u \cdot Q \cdot R_{rs}(\lambda)} + R_{surf}^{rs}(\lambda).
\]  

(3.4)
The variables $\sigma = 0.03$, $\sigma_L$, (calculated using the Fresnel equation for unpolarized light) and $\rho_u \in [0.50; 0.57]$ are reflection factors of the downwelling irradiance $E_d$, of the upwelling radiance $L_u$ and the upwelling irradiance in water $R_{rs}^-$. The factor $n_u$ denotes the refractive index of water and $Q$ describes the anisotropy of the light field in water and is set to 5 sr.

For deep water, $R_{rs}^-$ can be calculated as follows:

$$R_{rs}^-(\lambda) = f_{rs} \cdot w_b(\lambda),$$

with $f_{rs}$ as a function of the zenith angle in water $\theta'_{sun}$, the viewing angle in water $\theta'_v$ and $w_b(\lambda)$, which parametrizes the inherent optical properties of water:

$$w_b(\lambda) = \frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}.$$  

The variable $a(\lambda)$ denotes the absorption coefficient of natural water and $b_b(\lambda)$ the backscattering coefficient. The absorption coefficient is a function of the absorption coefficient of pure water, concentration of phytoplankton, CDOM and detritus and their corresponding specific absorption coefficients. Different phytoplankton classes can be fitted in WASI [Gege, 2014]. Since the measurement of water constituents during the field campaign did not distinguish between algal species, the spectrum 'dinoflagellates' was used in this study. CDOM is the concentration of dissolved organic matter. The absorption is approximated by multiplying the concentration $C_Y$ with an exponential function with the slope parameter $S$. Detritus refers to absorbing non-algal particles in water. The determining factors for $b_b(\lambda)$ are the backscattering coefficient of pure water and the concentrations of suspended particles and their corresponding specific backscattering coefficients. The particles in water are classified in WASI based on their scattering behaviour: type I exhibits arbitrary wavelength dependencies, specified by a spectrum incorporated from file and its concentration is denoted with $C_X$. The second class is comprised of particles that scatter proportional to $\lambda^n$ where the exponent of the scattering coefficient, $n$, is related to the size of the particles. The concentration of particle type II is denoted $C_{Mie}$.

If the remote sensing reflectance is calculated above shallow water, the variable $R_{rs}^h(\lambda)$ is substituted by $R_{rs}^{hW}(\lambda)$ in equation 3.4:

$$R_{rs}^{hW}(\lambda) = R(\lambda) \cdot \left(1 - A_1 \cdot \exp\left(-(K_d(\lambda) + K_{dW}(\lambda)) \cdot z_B\right)\right) + A_2 \cdot R^b(\lambda) \cdot \exp\left(-(K_d(\lambda) + K_{dW}(\lambda)) \cdot z_B\right).$$  

[Gege and Albert, 2006]

The constants $A_1, A_2$ were derived by radiative transfer simulations, the irradiance reflectance can be expressed by $R(\lambda) = R_{rs}^h$, $Q$ and $R^b(\lambda)$ summarizes the bottom reflectance effects, which can be fitted by adjusting the scaling factors of the different bottom types $fA[i]$. The diffuse attenuation coefficients for the downwelling irradiance $K_d(\lambda)$, the upwelling irradiance $K_{dW}(\lambda)$ (related to light field anisotropy caused by backscattering processes in the water) and $K_{dW}(\lambda)$ (caused by reflection at the bottom) are dependent on the inherent optical properties of water ($a(\lambda), b_b(\lambda), w_b(\lambda)$) and on the geometry of the light field, expressed by the cosine of the sun zenith angle in water.

$R_{rs}^{surf}$ denotes the spectral reflectance at the water surface. It is calculated as follows:

$$R_{rs}^{surf}(\lambda) = \rho_L \cdot \frac{L_s(\lambda)}{E_d(\lambda)},$$

with $\rho_L(\theta'_{sun}, \theta'_v)$ denoting the Fresnel reflectance calculated by the Fresnel equation for unpolarized light, $L_s(\lambda)$ is the sky radiance and $E_d(\lambda)$ denotes the downwelling irradiance. The parametrization of the downwelling irradiance distinguishes between the direct component $E_{dd}(\lambda)$ of the sun light and the diffuse component $E_{ds}(\lambda)$ of the sky light which is subject to Rayleigh and aerosol scattering, creating ambient radiation from the sky. The fit parameters $f_{dd}, f_{ds}$ represent the intensities of the irradiance components and are set to 1 for undisturbed illumination conditions. The sky radiance is calculated accordingly: the direct and diffuse components of $E_d$ are multiplied with the corresponding fit parameters $g_{dd}, g_{dsr}$ and $g_{dsa}$ and aggregated.
The sky glint and sun glint are then defined as follows: $\rho_L \cdot g_{dd} \cdot E_{dd}(\lambda)$ and $\rho_L \cdot (g_{dsr} \cdot E_{dsr}(\lambda) + g_{dsa} \cdot E_{dsa}(\lambda))$. For a detailed derivation of the cited formulas, please refer to [Gege, 2014; Gege and Albert, 2006].

The water depth $z_B$ can be analytically estimated to obtain start values for the fit. The wavelength interval from 600 to 650 nm is best suited for the calculation of $z_B$ using the following equation:

$$z_B = \frac{1}{2K_d(\lambda)} \ln \frac{A_1 \cdot R(\lambda) - A_2 \cdot R^b(\lambda)}{R(\lambda) - R^{sh}(\lambda)},$$

which is obtained by simplifying the equation 3.7 by assuming that $K_{uW}(\lambda) = K_{uB}(\lambda) = K_d(\lambda)$ [Gege, 2014, p. 55].

### 3.3.2 Inversion algorithm

The Downhill Simplex algorithm [Nelder and Mead, 1965] is implemented in WASI to determine the best parameter set during the inversion process. The calibrated and corrected remote sensing spectrum $m_i$ is fitted for each HySpex pixel by comparing it with the modelled remote sensing spectra $f_i$, which is calculated based on the chosen fit parameters and the remaining constant parameters. The fit parameters are adjusted until the residuum $r$ satisfies the pre-defined threshold, where the utilized residuum is calculated as follows:

$$r = \sum_{i=1}^{N} g_i \cdot |m_i - f_i|^2.$$

A constant function assigning 1 to the spectral weights $g_i$ is chosen and the residuum threshold is set to $5.00 \times 10^{-5}$ [Gege, 2015].

The Simplex space is constructed with $n + 1$ dimensions, corresponding to the $n$ fit variables of the inversion and the resulting residuum. The combination of all fit variables results in a set of the possible inversion curves, each curve being represented by one point in the simplex space. The objective is to find the point in the simplex space where the residuum is minimal. The algorithm searches for said point by considering the prior calculated curves and replacing the points where the residuum is maximal with new calculated positions. The advantage of the simplex algorithm is that the algorithm always converges and the computation times are low [Nelder and Mead, 1965; Gege and Albert, 2006; Albert and Gege, 2006].

### 3.4 Applied methodology

The following section describes the steps which are applied to derive the bathymetry and bottom classifications maps from the preprocessed HySpex and EnMAP image, corresponding to the green boxes in Figure 3.1.

#### 3.4.1 Sensitivity analysis for simulated data

The open source program Water Colour Simulator (WASI) is used to infer water depth and ground cover from the HySpex images. The version used in this thesis was specially extended with new options by Gege and is currently not available to the public. However, the description of the forward mode and sensitivity analysis is also valid for the newest public-domain version WASI 4.1 [Gege, 2015, 2004, 2014].

The forward mode of WASI allows for the calculation of remote sensing reflectance spectra based on the equations and fit parameters described in section 3.3.1. Up to three parameters with the corresponding value ranges can be set simultaneously as iterative variables.

In order the decide which parameters should be fitted and which bottom spectra represent the given conditions in the aerial HySpex image the most, a sensitivity analysis was conducted using the forward simulation to create theoretical spectra and evaluating the results in a subsequent inversion.

Figure 3.5 displays a exemplary forward simulation and the subsequent fit. The divergence between simulated and inverted water depth is the main decision criterion to decide which fit parameters are relevant.
and derive accurate results. The areal fraction of the fitted bottom types indicates, how much of the input bottom signal can be retrieved.

This mode is especially useful to evaluate the impact of the different bottom type spectra which were measured during the field campaign on the reflectance spectrum. WASI allows for six different bottom type parameters to be specified simultaneously. The main objective of the sensitivity study is to reduce the number of fit parameters as far as possible while still accounting for the changing conditions present in the test site. The reduction of fit parameters is advantageous because the fit is faster and the results are less corrupted by artefacts introduced by the ambiguity of the inversion: The measured signal contains the information of several synergistic processes which cannot be disaggregated easily. For example, the derived remote sensing reflectance spectrum exhibits two minima at 430 nm and 670 nm. These minima are attributed to the absorption by chlorophyll-a, which can be found in the water constituents (phytoplankton) or in the bottom (sea grass or mussels) or both. Neglecting the fit parameters which can simulate the observed absorption effects will likely lead to fit results which do not coincide with the real physical properties. Allowing too many parameters to be fitted however does not improve the reliability of the derived results: the fitted curve might be closer to the observed curve but the parameters chosen for the fit might not be present in the study site. The guiding principle 'as much as necessary, as little as possible' holds true. The strategy for finding adequate fit parameter is quite straight-forward.

First, a preliminary forward simulation with subsequent fit is conducted to evaluate the inversion ambiguity. Therefore, the remote sensing spectra are forward simulated for variable depths and bottom type compositions while defining the average of the measured water constituents as constants (see Figure 3.5a). The bottom types are roughly categorized in groups: bottom reflectance spectra which were derived for sand, clay or loam form the first group, the second group consists of the different mussel spectra and sea grass spectra are selected for the third group. The synthetic spectra are inverted utilizing the same bottom spectra form the simulation.

Second, different bottom compositions are simulated for each group and then fitted with with similar bottom spectra which are part of the bottom group. For example, a forward simulation is conducted to simulate coarse sand for shallow water regions varying from 0.1 m to 4 m in depth. 50 steps are defined, resulting in 50 different remote sensing reflectance spectra. These spectra are then fitted with the fine and coarse sand spectrum, adopting one additional bottom fit parameter for the inversion. In the next step, the fit results are evaluated. The mean of the fitted bottom types is calculated and the mean difference of the fitted and the simulated water depth is defined as quality criterion. The means of the bottom fractions $f[A]$ indicate which bottom types are used most during the inversion and therefore which bottom reflectance spectra has the most general features. Based on the quality criterion, it can be assessed which spectra can be substituted while introducing a reasonable small error. The remote sensing reflectance spectra created during the forward simulation are additionally fitted with different bottom type spectra, e.g. the fine and coarse sand forward simulation is then fitted with sandy loam or loamy sand.
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(a) Examplary forward simulation of remote sensing reflectance spectra iterating the water depth.

(b) Examplary fit of the forward spectrum corresponding to $z_B=3$ m.

Figure 3.5: Sensitivity analysis in WASI: Forward simulation of reflectance spectra (left) by varying the water depth and subsequent inversion with fit parameters (right). The fit parameters $z_B$, $C_Y$ and four bottom types are adjusted to approximate the shape of the input spectrum (blue curve). The difference of input water depth and retrieved water depth should be minimal for an accurate inversion.
CHAPTER 3. MATERIALS AND METHODS

Based on the resulting error in the fitted water depth, it can be decided which bottom spectrum can be applied as a general fit parameter for the bottom cover type. Since the forward simulation provides remote sensing reflectance spectra fast, many different bottom cover combinations can be simulated and fitted. After reviewing the water depth error, it can be decided which bottom spectrum provides the best inversion results for different bottom cover combinations.

Last, the chosen spectra which are most suited to represent their bottom type group are tested for bottom compositions which include all three groups and different water constituents. Additionally, the range from simulated water depths is adapted for a shallow (0.1 m to 4 m) and an intermediate scenario (0.1 m to 8 m) in order to investigate the depth dependency of the inversion accuracy. The water components which were investigated are the CDOM, the phytoplankton concentration, the concentration of suspended matter and the slope parameter of the CDOM absorption. The forward simulation scheme was designed to determine which water constituent parameter achieves a stable fit result. The fractions of the most suitable bottom spectra derived for each group were defined as constants. The water components were also set as constant. The subsequent fits were conducted with the same bottom type spectra and one to three activated water component parameters. The fits were evaluated by calculating the error in water depth and the average fraction for each bottom type. The decision which water components are the best choice for a fit parameter was based not only on the resulting water depth error but also if the bottom types were fitted without noise effects. The underlying assumption is that if the calculated bottom type averages diverge considerably from the evenly distributed input bottom fractions, then the fit parameters for the water components influence the fit negatively. Ideally, the fit with the smallest error in water depth should also exhibit a smaller error of the bottom type average values fractions.

3.4.2 Inversion strategy for HySpex data

Before conducting the inversion of the entire HySpex scene, small subset areas are defined based on the water depth and different bottom cover types visible in the RGB-representation (corresponding HySpex bands 60,35,15). Additionally, the under water pictures were evaluated for the bottom types. The subset images are used to test different fit parameter sets, based on the results of the forward simulations. The objective is to obtain the most suited parameter combinations depending on shallow and deep water regions. It is known from experience that the colour of the bottom cover influences the inversion results: bright bottom colour which is the case for sand reflects the downwelling irradiance to a higher degree as for example dark mussels. The higher amplitude of the reflected signal over sand leads to better detection of the bottom type and the water constituents. The influence of the bottom albedo is stronger for shallow water, therefore the fit parameters for ground cover are tested in subsets composed of variable bottom types in the shallow coastal region. On the other hand, the influence of water constituents is larger for deep water, as the signal travels through a thicker water column. The bottom cover fit parameters are chosen based on the fit results in the shallow water subset. Additionally, several water constituents are fitted: The concentration of phytoplankton, the concentrations of CDOM and suspended matter. Sun and sky glint affect the retrieved remote sensing reflectance as light is reflected at the crest of waves and due to the high temporal variability of the wave formation and the low pixel size of the HySpex sensor, the combined effect changes from pixel to pixel. The effects of sun and sky glint can be fitted with the parameters $g_{dd}$, $g_{dss}$ and $g_{dsa}$.

WASI saves the inversion result in ENVI-format with the file extension ‘.fit’. The fit results for the chosen parameters are stored as separate bands. Additionally, the residuum, spectral angle and the number of iterations are stored. The fit results can be loaded into WASI by adjusting the 2D options accordingly. The inversion results are displayed as colour-coded images, which can be stored and later used for the visual inspection for numerical artefacts or noise effects [Gege, 2014].
3.5 Validation

The validation of the inversion results is performed with the WASI option ‘Validation’. The sonar measurements are considered to be the ground reference and compared to the inversion results of the depth variable $z_B$. The data format for the validation data set needs to correspond to the image format: The geographical coordinates were given in the UTM format and the third column contained the measured sonar depth. WASI draws the sonar measurement points into the inversion results of $z_B$, using a colour coding specified in the menu ‘2D options’. Additionally, WASI creates a text file containing the image coordinates, the coordinates of the validation set, the validation variable and all fit parameters including the bands for the spectral angle, residuum and number of iterations.

The text file is analysed with a python script, providing different metrics and plots for interpretation. The metrics are defined as by Dörnhöfer et al. [2016].

The Root Mean Square Error (RMSE, equation 3.12) denotes the absolute difference of both water depths in m and is calculated as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (z_B(\text{sonar})_i - z_B(\text{HySpex})_i)^2}.$$  

(3.12)

Equation 3.13 shows the Mean Absolute Percentage Error MAPE, which states how large the HySpex depths deviates from the measured water depth in terms of percentage.

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{z_B(\text{sonar})_i - z_B(\text{HySpex})_i}{z_B(\text{sonar})_i} \right| \cdot 100$$  

(3.13)

Additionally, a linear regression is conducted by plotting the HySpex depths against the sonar depths. The linear least-square method is used and the resulting slope and y-axis intercept states how well the two data sets are alike. The intercept value can be interpreted as a measure for the systematic error introduced during the inversion process.

The last metric, Kendall’s $\tau$ is used to measure the correlation for ordinal datasets [The SciPy community, 2018a].

$$\tau = \frac{P - Q}{\sqrt{(P + Q + T) \cdot (P + Q + U)}}$$  

(3.14)

with $P$ being the number of concordant pairs, $Q$ the number of discordant pairs, $T$ the number of ties in dataset 1 (sonar water depths) and $U$ the number of ties in dataset 2 (HySpex estimates). Concordant pairs are defined as follows:

For two observations $(x_i, y_i)$ and $(x_j, y_j)$ sorted by $x$ with $i = 1, \ldots, n-1$ and $j = i+1, \ldots, n$ are concordant ($P$) if $x_i < x_j$ and $y_i < y_j$ is fulfilled. Discordant pairs ($Q$) meet the condition: $x_i < x_j$ and $y_i > y_j$. A tie $T$ in $Y$ is defined as follows: for $x_i \neq x_j$, $y_i = y_j$ and a tie $T$ in $X$ is defined as $x_i = x_j$ and $y_i \neq y_j$.

The Pearson product-moment correlation coefficient $r$ (equation 3.11) indicates how well the HySpex water depths $z_B(\text{HySpex})$ correspond to the measured sonar water depths $z_B(\text{sonar})$, where 1 denotes perfect agreement and $-1$ perfect negative correlation.

$$r = \frac{\frac{1}{n} \sum_{i=1}^{n} (z_B(\text{sonar})_i - \bar{z}_B(\text{sonar})) \cdot (z_B(\text{HySpex})_i - \bar{z}_B(\text{HySpex}))}{\sqrt{\frac{1}{n} \sum_{i=1}^{n} (z_B(\text{sonar})_i - \bar{z}_B(\text{sonar}))^2 \cdot (z_B(\text{HySpex})_i - \bar{z}_B(\text{HySpex}))^2}}.$$

(3.11)
4 | Results and interpretation

4.1 Choice of fit parameters

The semi-analytical approach with WASI for retrieving the water depth from the hyperspectral images requires the decision which parameters should be fitted and which can be treated as constants. This section summarizes the results of the applied sensitivity analysis and inversion of small image subsets and recommends fit strategies which are applicable under general conditions. The underlying research questions are which fit parameters are suitable for shallow and deep waters, how to derive a stable inversion and what accuracy can be expected of the inversion results.

4.1.1 Relevant bottom parameter

The influence of the spectral reflectance of the bottom on the received signal is considerable for shallow water regions. Consequently, the inversion of hyperspectral images over shallow water regions should account for different bottom spectra and therefore set a selection of bottom type spectra as fit parameters. The strategy how to determine the most suited type and combination of bottom spectra is described in section 3.4.2.

The different bottom types present in the study area were characterised by Schnalzger [2016] in 11
irradiance reflectance spectra, categorised in 3 groups for sea grass, mussels and sand bottoms. The bottom types for red and brown algae were excluded, as underwater images of the study area showed only an infrequent appearance of algae. The remaining bottom spectra which are evaluated with a sensitivity analysis are displayed in Figure 4.1. The results of the sensitivity analysis are summarized in the Tables A.1 and A.2.

The simulation of a uniform light-coloured mussel bottom with varying water depths and the subsequent inversion with both mussel types as fit parameter yields an averaged water depth difference of 0.43 m. A exemplary fit result is displayed in Figure 4.2. The fit parameters water depth and dark and bright mussel bottom type are adjusted during the inversion to fit the shape of the input reflectance spectrum. The deviation in water depth and bottom fraction for all simulated spectra are used to calculate the average difference in water depth and the mean bottom fraction.

![Inversion of forward-simulated spectrum](image)

**Figure 4.2**: Exemplary inversion of forward simulated reflectance spectrum in Wasi. The fit parameters water depth and light/dark mussels are adjusted to fit the blue curve.

Choosing the dark-coloured bottom as input parameter during the simulation yields a smaller mean depth difference of 0.4 m. WASI uses the both mussels spectra during the inversion, however the input bottom type is fitted with a higher average fraction in both cases. The simulation in conjunction with bright sediment as the second bottom type yields an averaged difference in $z_B$ of 0.33 m for the bright-coloured mussels and 0.45 m for the dark-coloured mussel spectrum. The last simulation combines both mussels spectrum and the same spectra are used during the inversion. The bright-coloured mussels spectrum is dominantly used during the inversion with an average fraction of 0.45 which is close to the defined input of 0.5. The dark spectrum is recognised with a fraction of 0.13, which is considerably lower than 0.5. Since the light-coloured mussel spectrum is recognised the most during the WASI inversion and the error in water depth is lower when a mixed bottom is simulated, the light-coloured mussel spectrum is chosen for the following inversions.

The same procedure is applied to derive the relevant sea grass spectrum. The averaged difference of $z_B$ for a uniform simulated bottom is smaller for the bright sea grass with 0.56 m, the dark sea grass spectrum yields 0.59 m. The dark sea grass spectrum is fitted with a 0.05 larger areal fraction when fitting the combination of dark and bright sea grass bottom cover. The mixed bottom in combination with the bright sediment spectrum and one of the sea grass spectrum yields a mean water depth difference of 0.57 m for the brighter spectrum and 0.61 m for the darker spectrum when the same bottom types are used as input and fit
parameters. Fitting the dark sea grass bottom type with the bright sea grass spectrum and keeping the bright sediment spectrum as second bottom type yields an error in water depth of 0.59 m. The difference in water depth for the other combination (simulating bright sea grass and fitting dark sea grass) is 0.6 m. Therefore, the bright and dark sea grass spectrum behave similarly but the calculated error in water depth is smaller when using the light-coloured sea grass spectrum as fit parameter. For that reason, the latter is chosen as the fit parameter for the sea grass bottom group.

The sensitivity analysis to derive the relevant sand spectrum includes different scenarios. First, the scheme described above is used to evaluate the dominating spectrum between coarse and fine sand as well as sandy loam (dark sediment) and loamy sand (bright sediment). Next, the dominating bottom spectrum is evaluated for a mixture of sediment and sand types. Since clay bottoms are rarely captured in the underwater photos, this bottom type is already excluded as a fit parameter. Last, all bottom types are simulated and fitted in conjunction.

The coarse sand spectrum is fitted with larger areal fraction for coarse sand as uniform input parameter with \( f_{A8} = 0.64, f_{A9} = 0.03 \). The fine sand is also dominating the fit result when used as input bottom type with \( f_{A8} = 0.19, f_{A9} = 0.43 \). The averaged water depth difference is 0.16 m and 0.19 m, respectively. The combination of both sand types and the subsequent fit shows, that the coarse sand spectrum is fitted with an areal fraction of 0.44 and the fine sand with 0.2.

The uniform bottom simulated with loamy sand and sandy loam is fitted predominately with the input spectrum \( (f_{A2} = 0.41, f_{A3} = 0.15 \) for a loamy sand bottom and \( f_{A2} = 0.01, f_{A3} = 0.67 \) for a sandy loam bottom). A mixture of both bottom types is mostly fitted by the loamy sand \( (f_{A2} = 0.41, f_{A3} = 0.21 \) with an averaged error in water depth of 0.36 m.

The results of the sensitivity analysis using the combination of two out of all four bottom types (fine and coarse sand, loamy sand and sandy loam) are that the fine and coarse sand are always fitted with a larger average fraction. The combination of three bottom types as input for the forward simulation yields different results: once both sediment types are included, the inversion yields the largest bottom fraction for the bright sediment (2: loamy sand). The averaged water depth error is circa 0.2 m for the sand dominated scenarios and circa 0.28 m for the sediment dominated scenarios. The last scenario, which is implemented with the combination of all sand and sediments types, yields that coarse sand and the dark sediment (sandy loam) are dominantly fitted with an averaged bottom fraction of 0.25 and 0.21. The average water depth error is 0.25 m.

To conclude, coarse sand is the overall dominating bottom type, followed by the fine sand and the bright sediment type (loamy sand). Since the sensitivity analysis was conducted under constant water and atmospheric parameters, the final fit parameters are derived by inverting small subset areas with variable bottom types and depth ranges.

Figure 4.3 displays the RGB-image of Zone 1 with the three subsets. The subset 1 was used to test different bottom parameter combinations, based on the results of the sensitivity analysis. By fitting only the bottom cover types and keeping water constituents and atmospheric parameters constant with the averaged values, high correlation coefficients are derived for all bottom cover compositions \( (r \in [0.77;0.83]) \).

Interestingly, the water depth maps show only minor difference although the bottom composition are varied from two to four different bottom reflectance spectra, as can be seen in Figure 4.4a. The derived
(a) Fit parameters: coarse sand, loamy sand, bright mussels, bright sea grass, $z_B$

(b) Fit parameters: coarse sand and bright sea grass, $z_B$

Figure 4.4: Exemplary fit results for the subset 1. The background colour corresponds to the fit result for $z_B$, the black line with the surrounding colour band displays the measured sonar water depths using the same colour coding.

Figure 4.5: Sensitivity analysis: Mean bottom reflectance and mean $z_B$ error (a) and relative $z_B$ error (b), based on the results of the sensitivity analysis displayed in Table A.1 and A.2.

Errors and correlation coefficients change also only little: The best metrics are derived for a bottom composition of coarse sand, loamy sand, bright-coloured sea grass and bright-coloured mussels ($r = 0.82, RMSE = 0.67m, MAPE = 22.90\%$) in comparison to the worst overall result ($r = 0.83, RMSE = 1.03m, MAPE = 26.14\%$). Reducing the bottom type fit parameters to the coarse sand and bright-coloured sea grass spectrum only, the following metrics are derived: $r = 0.77, RMSE = 0.77m, MAPE = 27.04\%$.

The inversion results of subset 1 indicate that WASI derives very stable water depths for variable bottom covers in bright and very shallow areas. Additionally, the inversion does not rely on the exact bottom type spectra but can tolerate some deviation between the real bottom cover and generalized bottom type spectra. Figure 4.5a displays the mean error of the inverted water depth in relation to the mean bottom reflectance, which is calculated by multiplying the derived areal fractions with the irradiance reflectance of the bottom types (see Figure 4.1) averaged from 400 to 700 nm. Inversions for higher averaged bottom reflectance yield lower mean errors in water depth. The mean water depth error is within range from 0.1 to 0.6 m for an averaged bottom reflectance of 0.9 % to 5.5 %. The sand/sediment bottom types generally exhibit higher mean bottom reflectance and lower absolute and relative errors mostly in the range of 15 %. 

4.1. CHOICE OF FIT PARAMETERS

4.1.2 Relevant water parameters

The bottom type combinations were the basis for a second sensitivity analysis, where the water depth was varied from 0.1 m to 8 m depth. The water constituents were now fitted during the inversion of the synthetic spectra, together with the bottom types and the water depth. The forward scheme was designed to test the fit performance of one to three water parameters and the parameter $f_{ds}$ for spectra produced with varying bottom types. The results are summarised in Table A.3.

The activation of the fit parameters $C_X$ and $f_{ds}$ lead to averaged water depth errors in the range from 0.98 m to 2.80 m for varying bottom compositions and activated/deactivated CDOM absorption as fit parameter. The mean depth error is in the range from 0.26 m to 0.4 m when fitting the CDOM absorption with the parameter $C_Y$, keeping $C_X$ and $f_{ds}$ constant and varying the bottom composition. The combination of $C_Y$, $S$ or $C_{dino}$ yield depth errors in the same range as when fitting only $C_Y$. The smallest error in water depth with 0.26 to 0.28 m could be derived for bottom covers including both sand spectra, therefore a high amount of bright bottom types is favourable for the inversion process.

The influence of absorption and scattering by water constituents on the total remote sensing signal increases for deeper water regions, which is why different fit parameters for water constituents are tested during the inversion of subset 3. The subset 3 lies in a region with 3 to 6 m deep water, which is optically darker than subset 1 but quite clear as the sand bottom is still visible. Two different flight stripes are overlapping in this regions which is visible on sharp boundary of masked out areas (white pixels) in the left part of the image. Figure 4.6 displays exemplary fit results for the parameter water depth with the subset 3 as input. Table B.1 summaries the applied inversion scenarios and the corresponding $r$, $RMSE$ and the slope and intercept of the regression line. First, only bottom cover and water constituents were fitted. All combinations resulted in unsatisfying metric values with negative correlation coefficients for the water depth. The resulting water depth map was noise affected, which can be seen by the ‘granular’ appearance of the water depth in Figure 4.6a and 4.6b. To address these effects, surface parameters should be included as fit parameters. The following section describes which surface parameters are best suited for the inversion.

4.1.3 Relevant surface parameters

The boundary between the neighbouring flight stripes caused a jump in the fit parameter values, indicating that the atmospheric correction imposes a limitation for the inversion process. Even though the sand bottom is still visible in the RGB-image 4.3, the best settings of subset 1 resulted in poor metric values and an unstable inversion as can be seen in Figure 4.6a. This outcome underlines the increasing influence of the water constituents (Figure 4.6b), and more importantly the importance to fit glint effects (Figure 4.6c,4.6d). Fitting the intensity of the downwelling irradiance with $f_{dd}$ or $f_{ds}$ for the direct and diffuse part resulted in an overestimation of water depth at the boundary of the two flight stripes as can be seen in Figure 4.6c.

Keeping $f_{dd}$ and $f_{ds}$ constant and fitting $g_{dd}$ results in the smallest errors with $RSME = 0.96m$, $MAPE = 11.3\%$ and the slope closest to 1 with 1.18.

Last, the subset 2 was inverted using the fit parameter sets which performed well for subset 1 and 3. The measured water depth is circa 8 to 11 m in subset 2. It was expected that the fit parameters for subset 3 were a good approximation. Instead, negative or very small correlation coefficient ($r \in \{-0.02;23\}$) and very large relative errors with $MAPE \in [210%;500\%]$ were found for inversions which fitted either $f_{dd}$, $f_{ds}$ or $g_{dd}$. Most parameter combination tested resulted in noisy or artefact affected water depth results, indicating an unstable fit. The calculated errors and correlation coefficients were not consistent for the different inversion runs, e.g. large $MAPE$ values were derived for the run with the highest correlation coefficient. The results indicate that optically dark and non-shallow water regions are difficult or impossible to invert.

4.1.4 Recommended fit parameters

Table 4.1 summaries the recommended fit parameters for shallow and deep water regions based on the bottom reflectance spectra and water components measured in the German Baltic Sea. The number of bottom type fit parameters depends largely on the site specific heterogeneity. Sand bottom types derived
(a) Fit parameters for g3n_1: coarse sand, loamy sand, bright sea grass, bright mussels and $z_B$

(b) Fit parameters for g3n_5: coarse sand and bright sea grass, $C_Y, C_{dino}, z_B$

(c) Fit parameters for g3n_14: coarse sand and bright sea grass, $C_Y, C_{dino}, f_{dd}, z_B$

(d) Fit parameters for g3n_21: coarse sand and bright sea grass, $C_Y, C_{dino}, g_{dd}, z_B$

Figure 4.6: Exemplary fit results for the subset 3 (see Table B.1). The background colour corresponds to the fit result for $z_B$, the black line with the surrounding colour band displays the measured sonar water depths.

lower mean water depth errors in comparison to mussels and sea grass (see Table A.1 and A.2), therefore fitting sandy bottom types is recommended. Other bottom types can be chosen depending on the site-specific characteristics. The retrieval of bottom signal over water areas deeper than the Secchi depth is only expected for bright bottom types like sand. Based on the sensitivity results for water constituents (see Table A.3), the fit of CDOM absorption and phytoplankton concentration is recommended. However, the fit of the slope of the CDOM absorption $S$ in combination with the $C_Y$ and $C[0]$ provides the most accurate fit of the water depth. This combination can be chosen when only one or two bottom types are fitted to keep the total number of fit parameters small and the inversion stability high. Since not all atmospheric effects can be removed during the correction, it is advised to fit the glint effects with the parameter $g_{dd}$ for both shallow and deep water areas.

<table>
<thead>
<tr>
<th>Recommended fit parameters</th>
<th>Bottom types</th>
<th>Water constituents</th>
<th>Surface parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shallow water $z_B \in [0;5.7]$ [m]</td>
<td>x x x (x)</td>
<td>x x (x)</td>
<td></td>
</tr>
<tr>
<td>Deep water $z_B \in [5.7;11.4]$ [m]</td>
<td>x (x)</td>
<td>x x (x)</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.1: Recommended fit parameter for shallow and deep water regions based on the results of the sensitivity analysis. The recommended bottom type for A in the Baltic Sea is coarse sand, for B bright sediment, for C bright sea grass and for D bright mussels.

4.2 Bathymetry

Different fit parameter sets were tested for every scene and the best inversion result was determined by comparing the fitted water depth with the ground reference. Section 4.2.1 presents the best derived bathymetry maps for all HySpex zones and the simulated EnMAP scene and section 4.2.2 evaluates the accuracy of the water depth.
4.2. BATHYMETRY

4.2.1 Water depth maps

Zone 1: shallow with sandy bottom cover  Figure 4.7 shows the inversion results of the water depth for the zone 1, where the water depth retrieval yielded the best results for all HySepx zones. The corresponding fit parameters and constants are listed in the column run 8 of Table B.3, and a comparison with independent water depth measurements using echosounding is presented in section 4.2.2. Additionally, the sonar measurements are included applying the same colour scheme. The sonar depths are only distinguishable in regions where the inversion derived water depths fall into a different colour category. The central and shallow part of the zone show good agreement with the sonar measurements. The beach area visible in the RGB-image in Figure 4.7a is mapped as shallow regions with water depths smaller or equal to 1 m. The water depth increases gradually towards the north-east, and with steeper gradient towards the western and eastern part. There, the sonar water depths show disagreement with the inversion result, as the inversion seems to overestimate the real water depth towards the south and underestimate it towards the north. The structures mapped in the shallow regions coincides very well with the impression of the depth in the RGB-image in general. The bathymetry map shows shallow structures which are barely visible in the RGB-image, for example a small vertical elongated area with a water depth ranging from 2 to 5 m to the East of the land mass (marked as region A in 4.7). A second area located in the North at the image centre is of interest, as it shows a crescent-shaped structure which is less affected by vertical stripes, marked as region B. This indicates that the water depth result is quite stable in this area, suggesting a reliable bathymetry of 5 to 10 m. The horizontal striping visible in the eastern and western part of the image display high water depths and are likely inversion artefacts. The occurrence of artefacts and inversion ambiguities will be addressed in section 4.4. Since most sonar measurements in zone 1 were conducted in the shallow part, the averaged measured water depth is 4.1 m (see Figure 3.4) and therefore, it seems reasonable that the inversion results for zone 1 showed the smallest error of the retrieved water depth. Additionally, bright sand structures are visible in the RGB-image displayed in Figure 4.7a, which provide higher remote sensing reflectance values and facilitate the inversion.

Zone 2: shallow to deep with sand/mussel bottom cover  The inversion of the zone 2 with the settings listed in the column run 3 in Table B.4 yields a bathymetry map with fit results similar to the results of zone 1: the shallow water regions displayed in Figure 4.8b correspond well to the bright areas of the RGB-image. The depth increases quite rapidly from the shallow land bank which seems to be covered in sand and mussels with less then 1 m water depth towards the South with water depths between 15 and 20 m. The sand bank phases out towards the north and exhibits water depths of mostly 2 to 5 m. The discrepancies between mapped water depth and sonar measurement are most abundant in the 5 to 10 m water depth regions in the centre of the zone (see Figure 4.17), where the inversion underestimates the true depth in the northern part and overestimates the water depth in the southern part. However, the shallower water area corresponding to the small bright patch in the northern part of the RGB-image was mapped to the correct water depth interval between 5 to 10 m. The sonar measurements were predominantly conducted in the deeper water areas, resulting to a mean water depth of 8.1 m. Therefore, the water depth retrieval in the centre part of the zone was assumed to be difficult, which is also reflected in the bathymetry result. The artefact stripes occur in the deeper parts of the zone, to the east and to the south. Additionally, the inversion results traces the boundaries of the different flight stripes, leading to different depth values especially in the eastern part of the zone. This effect is less pronounced in the shallow water area with an water depth of 2 to 5 m.

Zone 3: intermediate water depth with mussel bottom cover  Figure 4.9 shows the bathymetry results of the zone 3 derived by using the settings listed in the column run 4 of Table B.5 in comparison to the RGB-image.

The derived bathymetry overestimates the water depth in all areas except for the slim beach strip and 2 to 5 m water area in the southern part of the zone (see Figure 4.19). There, the water colour is brighter and the bottom cover appears to be sand. The results are quite different to the other zones although the
Figure 4.7: RGB-display of zone 1 (a), Bathymetry map and colour-coded sonar measurement (overlying lines) of zone 1 (b). The positions of the sonar measurements are displayed in Figure 3.3.
Figure 4.8: RGB-display of zone 2 (a), Bathymetry map & colour-coded sonar measurement (overlying lines) of zone 2 (b). The positions of the sonar measurements are displayed in Figure 3.3.
same fit parameters except for one bottom type were chosen. The derived bathymetry does not reproduce the overall depth characteristics of the coastal area. The average measured water depth is 6.5 m and the area along the coast line is quite shallow with values shallower as the averaged Secchi depth. Therefore, the real depth conditions are similar to the zone 2. The artefacts appear throughout the zone and the divergence of the derived water depth to the real water depth is partly greater than one depth interval in the colour scale. The RGB-image is very dark in zone 3, comparable to the southern image part of the RGB-image of zone 2. This image part exhibits also artefact stripes, however to an lesser extent than in zone 3.

In order to answer why the inversion failed in zone 3, the difference in bottom cover is investigated. Several bottom cover samples were collected throughout the zones 1 and 2. Dark bottom cover like mussels are quite abundant in zone 2, as can be also seen at the brownish patches in the <= 1 m water depth area the RGB-image 4.8a.

Increasing the contrast of the remote sensing reflectance in zone 3 allows for an estimation of the bottom cover type. The corresponding RGB-image is displayed in Figure 4.10. The roughness and colour suggest a bottom cover composed of mussels. Consequently, the inversion run which applied the mussels bottom cover resulted in the best RMSE and MAPE values for zone 3.

A non-public mode of WASI offers a different way to derive the bottom albedo present in the image based on known water depth, water constituents and surface parameters. A shallow, homogeneous region covered with mussels was selected and the option 'Derive bottom albedo' was activated for this purpose. The water depth was set to the measured wa-
4.2. BATHYMETRY

Figure 4.11: Exemplary remote sensing reflectance spectrum of a shallow water pixel dominated by the bottom type mussels.

The most likely cause for the failed inversion lies in the magnitude of the remote sensing reflectance above the assumed mussel bottom cover. Figure 4.11 displays an exemplary remote sensing reflectance spectrum of HySpex and the corresponding fit using the same fit parameters as in the best run 4. First, it is apparent that the magnitude of the signal is very small. Small errors in the atmospheric corrections affect therefore the HySpex signal to a larger extent. Additionally, the HySpex signal assumes very low values near the infra-red but increases in higher channels. The water absorbs sunlight in the infra-red therefore the HySpex signal should not increase but behave like the modelled WASI fit curve. The HySpex signal assumes small values around the 700 nm channel to such an extent that the model is not capable of fitting the curvature. Since the reflectance signal is only of magnitude 0.5 %, it lies likely in the uncertainty range from the atmospheric corrected signal. The uncertainty of the remote sensing signal is discussed in section 5.1.

EnMAP-simulated scene Figure 4.12 displays the best bathymetry map of the EnMAP-simulated scene. The fit parameters and settings are listed in Table B.2 in the column run 1. The depth results resemble the findings of the HySpex zones. Similar depth values were derived in the shallow regions of zone 1 and zone 2. The inversion failed in the area of zone 3, where the water depth is again overestimated in general. All deep-water areas of the EnMAP-scene are affected with artefact stripes, as can be seen best in the north western part and the centre south. Interestingly, the transition between two neighbouring flight lines in zone 1 is not distinctly visible as it is in Figure 4.13a. A similar effect can be observed in the area of zone 2, where the boundary between both flight stripes in the centre of zone 2 does not lead to jumps in the bathymetry results. The structures of shallow regions are similar to the HySpex results in zone 2, but exhibit partly larger areas of shallow water depth, e.g. in the 2 to 5 m range.
Figure 4.12: RGB-display of EnMAP simulated scene (a), Bathymetry map and colour-coded sonar measurement (overlying lines) of the EnMAP-simulated scene (b). The positions of the sonar measurements are displayed in Figure 3.3.
4.2. BATHYMETRY

Detailed bathymetry maps  A detailed overview of the shallow water areas of all HySpex zones and the EnMAP-simulated scene is displayed in Figure 4.13. A mask for shallow water areas was derived by excluding the water depths results which are larger than 5.8 m, which is the averaged Secchi depth measured in zone 1 and 2. This threshold was chosen somewhat arbitrary, as the local Secchi depth might diverge significantly from this value. However, the maps in Figure 4.13 should underline to what detail bathymetry structures are visible and the averaged Secchi depth seems to be a good measure for 'shallow’ and therefore structurally more complex regions.

Figures 4.13a and 4.13b reproduce the sand dunes visible in the RGB-images very well. The influence of the different acquisition geometry at neighbouring flight stripes also becomes more apparent. Interestingly, the horizontal stripes caused by artefacts introduced during the inversion are absent in all HySpex zones, and only minimal in the EnMAP-simulated scene. Looking at the detailed representation of the HySpex zone 3 underlines that the inversion process was not able to detect the water depth correctly except for the very limited coastal area where the bottom seems to be covered in sand. The same holds true in the EnMAP-simulated scene. In general, the EnMAP-simulated scene reproduces a bathymetry map very similar to the ones derived from the HySpex scenes, although some shallow areas appear to be larger and less deep than in the HySpex-scenes, e.g. the small region in the HySpex zone 1 to the south-east of the coast appears to be larger in extent and is mapped in yellowish colours instead of reddish colours. This effect is most apparent in the region of zone 2, which was mostly mapped to bathymetry values smaller than the averaged Secchi depth in the EnMAP-simulated scene whereas the HySpex zone shows distinctively clearer boundaries between shallow and non-shallow regions.

To summarize, very good agreement of the EnMAP and HySpex scenes in terms of bathymetry retrieval indicates that the EnMAP scenes are capable of mapping complex bathymetry structures to a similar degree as the airborne HySpex imagery, assuming that the EnMAP-products will coincide with the simulated EnMAP scene.
Figure 4.13: Bathymetry maps and insitu depths for shallow regions (depth $\leq 5.7$ m).
4.2.2 Water depth accuracy

The best derived bathymetry in run 8 for zone 1 coincides very well with the measured sonar water depths up to the averaged Secchi depth of circa 5.7 m. At greater depths, the fit results are less accurate as the true water depth are both under- and overestimated, as can be seen in Figure 4.14a.

The yellow colour indicates a high density where the derived water depths coincide very well with the sonar measurements and lie on the 1:1 line. The scattering around the 1:1 line is in the same range up to the Secchi depth and increases afterwards with the increasing water depth as can be seen in the standard deviation in Figure 4.14b. The derived correlation coefficient calculated for water depths larger than the Secchi depth and smaller than twice the Secchi depth (intermediate water depth range) indicate a weak correlation with \( r : SD < zB < 2 \cdot SD = 0.36 \) (see Table B.3). The corresponding RMSE is 3.88 m. The result of the linear regression calculated for water depths up to twice the Secchi depth yields a slope of 1.15 and an y-axis intercept of -0.35 m. Differentiating between regions which are shallower than the averaged Secchi depth yields a correlation coefficient of 0.90 and a RMSE of 0.64 m. Evaluating the absolute mean percentage error MAPE yields 13.26 % for shallow water regions and 29.63% error for the intermediate water depth range. The mean value of the difference of the fitted water depth and the measured water depth was calculated in a binning interval of 50 cm and is depicted with the blue triangle. The mean of the water depth differences fluctuates around the 0 within a 0.25 cm range until a water depth of circa 4.5 m. For values deeper than the Secchi depth, the mean of the water depth difference first increases until a water depth of circa 8.5 m, corresponding to an overestimation of approximately 4 m during the inversion process. The overestimation is still present for deeper water regions but decreases in magnitude before transitioning to an underestimation with negative mean values. The standard deviation increases with water depth in general. A quite high standard deviation was derived in the depth of 2.6 m.

The results for the EnMAP-simulated scene in run 1 for zone 1 are quite similar (see Table B.2 and Figure 4.14c, 4.14d): the Pearson correlation coefficient between measured water depths and the derived water depths is 0.94 for water depth values equal or smaller than the Secchi depth. The slope of the linear regression equals to 1.03 and y-axis intercept equals to -0.31 m and indicates a fit result with small systematic error. The fitted water depths scatter increasingly with the real water depth, as can be seen in Figure 4.14c, therefore the correlation coefficient for intermediate water depths is quite small with 0.47. The resulting RMSE yields 3.44 m, which is a little bit smaller compared to the result for the HySpex scene. The MAPE is smaller for shallower water areas with 12.65 % and slightly larger for intermediate water depths with 31.17 %.

The mean and standard deviation displayed in Figure 4.14d, calculated for the difference of HySpex water depth and sonar water depth are similar to the HySpex results. However the standard deviation is smaller in the EnMAP scene until the Secchi depth and the mean difference is smaller for water depths larger than the Secchi depth. This might be connected to the process of averaging the measured sonar depths for on EnMAP pixel. Since most sonar measurements were conducted in the shallow areas, the averaging effect reduces the standard deviation in the 1 m binning interval.

Figure 4.15 displays the density plot and the mean and standard deviation of the relative difference between HySpex and EnMAP-derived water depth and measured sonar water depth, respectively. Again, the EnMAP results are similar to the HySpex image. Most points scatter within +0.2 and -0.2. The averaged relative water depth error is smaller than 20 % up to circa 6 m for the HySpex result and up to 7 m for the EnMAP scene. The largest relative error derived from the HySpex image is +0.6, calculated for the water depth interval of 7.5 m to 8.5 m. The EnMAP fit result exhibit the largest relative error of 0.4 at circa 8 m.

The water depth retrieval for zone 2 is less accurate in comparison to zone 1 (see Table B.4, Figure 4.16). The correlation coefficient for for depths until the Secchi depth is 0.82 and for intermediate water regions 0.28. The correlation coefficient derived in zone 2 of the EnMAP-simulated scene in run 1 is higher shallow water areas with \( r = 0.91 \) and smaller for intermediate water depths with \( r = 0.26 \). The MAPE of 19.34 % indicate less accurate results in the shallow areas in comparison to zone 1 but a higher accuracy in the intermediate depths with 21.1 %. The MAPE derived for the inversion result of the EnMAP-simulated scene is larger when calculated for intermediate water depths: MAPE = 42.28% and smaller for shallow regions.
Figure 4.14: Bathymetry results for zone 1 and EnMAP-simulated scene: Density plots (a, c) and mean and standard deviation (b, d) of the derived water depth with a 0.5 m binning interval for the Hyspex zone (a, b) and 1 m interval for the EnMAP scene (c, d). The corresponding fit parameters are listed in Table B.2 and B.3. The density plots are colour-coded based on the probability density derived with a Gaussian kernel function [The SciPy community, 2018b].
Figure 4.15: Bathymetry results for zone 1 and EnMAP-simulated scene: Density plots (a, c) and mean and standard deviation (b, d) of the water depth difference with a 0.5 m binning interval for the Hyspex zone (a, c) and 1 m interval for the EnMAP scene (b, d). The density plots are colour-coded based on the probability density derived with a Gaussian kernel function [The SciPy community, 2018b].
Figure 4.16: Bathymetry results for zone 2 and EnMAP-simulated scene: Density plots (a, c) and mean and standard deviation (b, d) of the derived water depth with a 0.5 m binning interval for the HySpex zone (a, c) and 1 m interval for the EnMAP scene (b, d). The corresponding fit parameters are listed in Table B.2 and B.4. The density plots are colour-coded based on the probability density derived with a Gaussian kernel function [The SciPy community, 2018b].

with \( \text{MAPE} = 15.11\% \). The \( \text{RMSE} \) of Zone 2 in shallow regions is 1.16 m (HySpex) and 0.72 m in the EnMAP simulated scene and therefore larger compared to zone 1. The \( \text{RMSE} \) for intermediate water depths is 2.57 m in the HySpex zone and 4.28 m in the simulated EnMAP scene. Still, the water depth retrieval was quite accurate for regions shallower as the Secchi depth, as can be seen in the density plots in Figure 4.16a and 4.16c. The retrieved water depths follow the 1:1 line until circa 4 m sonar depth. For deeper water regions, the scattering increases and the depth is overall underestimated. The underestimation becomes more evident in the EnMAP-simulated scene, especially in Figure 4.16d. The number of sonar measurements is reduced when all depth values in one EnMAP pixel are averaged. This leads to the calculation of a small deviation of water depths until 4 meter. The difference of measured and derived water depth declines then almost linearly starting from 4 m sonar depth. Interestingly, the standard deviation of the water depth difference is reduced for all water depths considerably.

Figure 4.17 displays the relative water depth error for both HySpex and EnMAP results in a density plot and the calculated mean and standard deviation in Figure 4.17b and 4.17d. The averaged relative depth error assumes values in the range from +0.25 and -0.25 for the HySpex fit result. The EnMAP inversion exhibits mean relative depth errors ranging from 0 to -0.52. The up-sampling of the sonar measurements for the 30 m x 30 m pixel size leads to a reduction of scattering as can be seen in Figure 4.17c and 4.17a. The
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Figure 4.17: Bathymetry results for zone 2 and EnMAP-simulated scene: Density plots (a, c) and mean and standard deviation (b, d) of the water depth difference with a 0.5 m binning interval for the Hyspex zone (a, c) and 1 m interval for the EnMAP scene (b, d). The density plots are colour-coded based on the probability density derived with a Gaussian kernel function [The SciPy community, 2018b]

underestimation of the water depth in the EnMAP scene leads therefore to greater relative errors.

The zone 3 yields the worst water depth accuracy for both HySpex (run 4) and simulated EnMAP scene (run 1) (see Table B.5, Figure 4.18). As can be seen in Figure 4.18a and 4.18c, the inverted water depths overestimate the true water depth significantly. The corresponding correlation coefficients for shallow water depths assumes 0.58 for the HySpex zone and 0.54 for the EnMAP scene. Including only the intermediate water depths impairs the correlation coefficients with 0.13 for HySpex and 0.25 for the sublimated EnMAP scene.

The mean absolute percentage error assume very large values for the shallow regions, with $\text{MAPE}_{\text{HySpex}} = 192.32\%$ and $\text{MAPE}_{\text{EnMAP}} = 98.66\%$. The corresponding $\text{RMSE}$ is 10.16 m for the best inversion run of zone 3 and significantly better for the simulated EnMAP scene with 6 m. Again, this can be attributed to the same cause mentioned for the zone 2: the averaging of sonar measurements for the EnMAP scene reduces the total amount of points and therefore the mean and the standard deviation of the difference of inverted water depth and sonar water depth is reduced. The Figures 4.13c and 4.18d illustrate this effect. The Both HySpex and EnMAP results overestimate the water depth. The smaller overestimation in the EnMAP scene can be attributed to the different fit parameters: the entire EnMAP scene was inverted using the sand and sea grass bottom cover as fit parameters, whereas the best inversion run for zone 3 was conducted using the mussel bottom cover instead of the sea grass bottom type. Additionally, the reduced number of measure-
Figure 4.18: Bathymetry results for zone 3 and EnMAP-simulated scene: Density plots (a, c) and mean and standard deviation (b, d) of the derived water depth with a 0.5 m binning interval for the HySpex zone (a, c) and 1 m interval for the EnMAP scene (b, d). The corresponding fit parameters are listed in Table B.2 and B.5. The density plots are colour-coded based on the probability density derived with a Gaussian kernel function [The SciPy community, 2018b]

ment points after the averaging over one EnMAP pixel does not always ensure a meaningful statistic in some parts of the scene, e.g. in the deep water parts of zone 1 and also in zone 3. The inversion results for zone 3 exhibit the largest mean relative water depth error with values in the range from -0.5 to 2.6. Interestingly, the inversion predominately failed in the shallow water regions and the mean error is reduced with an increasing water depth.

To summarize, the water depth accuracy depends not only on the water depth but also on the environmental conditions, predominately on the brightness of the bottom type. The \( RMSE \) in the shallow areas ranges from 0.56 to 6 m for the simulated EnMAP scene and from 0.64 m to 10.16 m for the HySpex scenes. The relative water depth error ranges from -0.52 to +2.6 including all outliers. Focusing on the HySpex results of zone 1 and 2 yields an averaged relative depth error of +/-0.25 up to 7 m water depth. The EnMAP inversion results yield an averaged relative error from -0.4 to 0 in the same depth interval.

### 4.3 Bottom classification

The accuracy of the bottom classification is difficult to assess, since only isolated under-water photos are available. The RGB-representation of the hyperspectral images enables a visual distinction between sandy
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Figure 4.19: Bathymetry results for zone 3 and EnMAP-simulated scene: Density plots (a, c) and mean and standard deviation (b, d) of the water depth difference with a 0.5 m binning interval for the Hyspex zone (a, c) and 1 m interval for the EnMAP scene (b, d). The density plots are colour-coded based on the probability density derived with a Gaussian kernel function [The SciPy community, 2018b]
bottom types and dark bottom types. Therefore, the plausibility of the sand bottom type results can be evaluated, which is not possible for the mussels or seaweed bottom type. The inversion process was restricted to assign values of the areal fraction $f_A$ ranging from 0 to 2 for each bottom type, where a 1 is assigned if the bottom reflectance spectrum of the database models the contribution of the bottom reflectance effect $R^b(\lambda)$ perfectly for pixels for which the bottom is cover to 100% by a single substrate. The upper limit was set to 2 to allow the classification of bottom types which are brighter as the input spectra. Basically, the assigned values are scaling factors for the database reflectance spectrum, where higher values indicate a brighter bottom surface and low values suggest that the chosen bottom type does not match the measured signal well. For so called mixed pixels which are composed of different substrate types, the sum of the different bottom type fractions was defined to yield values ranging from 0.5 to 2. As a result of 4.1, the maximum number of substrate types was set to 2; these substrates were coarse sand and light-coloured sea grass or light-coloured mussels.

The same zones are classified as in section 4.2.1 and the corresponding fit parameters are listed in Tables B.2, B.3, B.4 and B.5. First, an overview of all results of the bottom type fit parameters is presented for all zones in Figures 4.20 and 4.21 and the plausibility of the inversion result is evaluated. Second, the dominating bottom type is assessed as a function of the water depth.

Figure 4.20 displays the fraction of the bottom type coarse sand for all HySpex zones and the simulated EnMAP scene. Since the reflectance spectrum of coarse sand is also used to model bright sand, the fit cannot distinguish between different sand types and the related fit parameter $f[A]$ is affected by the brightness of sand in addition to the areal fraction within a pixel. The sand ripples are clearly visible in the centre of zone 1 and 2, where sand areas were identified with $f[A]$ values ranging from 0.8 to 1.5. In general, the displayed sand structures in the shallow regions coincide very well with the RGB-images and the large sand area towards the north is displayed accurately in both zones. No clear sand structures are visible in zone 3 except for a small area in the south-east. The bottom classification is affected by stripes in the entire zone 3 and in the deep water regions of zone 1 and 2.

Higher scaling factors were mostly obtained in deep water regions, where the bottom classification is unreliable or impossible due to the attenuation of the bottom reflectance signal in the water column. Therefore, not the real contribution of the bottom reflectance to the total signal was obtained during the inversion. Further, the clear boundary between neighbouring flight stripes displayed by the abrupt jumps in the fitted scaling factor indicates that atmospheric effects like sun or sky glint dominate the bottom classification in deeper water regions. Therefore, the displayed scaling factors have no physical meaning in the deeper water areas.

To exclude the regions where the bottom classification is assumed to be limited or impossible since the water is too deep, Figure 4.20d displays the derived sand cover only for water regions, where the inversion process retrieved water depths smaller or equal to the average Secchi depth of 5.7 m. The sand cover map for the EnMAP scene is similar to the results of the HySpex zones. Both geometrical structures and intensity are preserved in the EnMAP scene. The comparison with the RGB-image of the EnMAP scene (Figure 4.12a) shows that all major sand structures are detected. The geometrical structures are best reproduced for brighter sand areas.

Figure 4.21 shows the inversion results for the bottom type sea grass for zone 1, 2 and the EnMAP scene and the mussel bottom type for the zone 3. The $f[A]$ values in the shallow regions range mostly between 0.2 and 0.8 for zone 1. There, higher values are only found in the deep water regions and are affected by horizontal stripping. Higher scaling factors were derived in the very shallow water parts on zone 2, where the RGB-image indicates a greenish/brownish bottom cover type. The remaining areas exhibit similar scaling factor ranges with low values in the shallow parts and high, noise-affected values in the deep water region. Zone 3 yielded the best inversion using the mussels spectrum as second bottom type. The entire zone is affected by vertical striping where the scaling factor was mostly fitted with values exceeding 0.8. A small area in the south-east stands out being stripe-free. This area was also stripe-free in the sand cover map and yielded high sand fraction values up to 1.5.

The EnMAP scene was fitted using sea grass as second bottom type since the majority of zones achieved
Figure 4.20: Sand cover maps for HySpex zones and for shallow regions of the EnMAP simulated scene.
Figure 4.21: Sea grass and mussel cover maps for the HySpex zones and shallow regions of EnMAP simulated scene
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better results using this bottom type and the bottom classification failed anyway in zone 3. Again, the bottom cover is only displayed for depths smaller or equal to the averaged Secchi depth of 5.7 m. The sea grass map yielded very similar results in comparison to the HySpex scenes. However since the EnMAP pixels are significantly larger, some small scale structures like in the shallow part of zone 2, where the $f(A)$ values assumes values in the 1 to 1.5 category, are reduced to isolated pixels.

The plausibility of the bottom cover inversion result is difficult to evaluate. The under-water photos show that sea grass and mussels are abundant besides sandy bottom types. However, the heterogeneity of the sea bottom makes it challenging to differentiate between different bottom type classes, which is emphasised by the result of the sensitivity analysis. Therefore, low scaling factors of sea grass might indicate the occurrence of isolated sea grass patches in the pixel or darker mussel banks. The detection and classification of non-sandy bottom types is very challenging, as heterogeneity of water constituents which might include varying phytoplankton or suspended matter concentrations are difficult to address during the inversion.

In order to investigate a possible relation between dominating bottom type and depth, the pixels where sonar measurements were conducted are evaluated for their dominating bottom type and then plotted against the measured depth. The dominating bottom type was assigned to the bottom spectrum which was fitted with the largest $f(A)$ values during the inversion. The result is displayed in Figure 4.22, the left side showing the results for the HySpex zones and the right side displaying the results for the EnMAP simulated scene.

The Figure 4.22a and 4.22b show similar results for zone 1. The dominating bottom type for shallow water and deep water is coarse sand and sea grass, respectively. The scattering of both bottom types increases with water depth in the HySpex zone while the scattering seems to be a little bit larger for the sea grass bottom.

The results for the dominating bottom type for the EnMAP scene in zone 2 deviate from the HySpex results, as can be seen in Figure 4.22d and 4.22c. The sea grass bottom type dominates until circa 3 m water depth. For deeper water areas, most pixels exhibit sand bottom until a water depth of 10 m, where the sea grass bottom type was fitted in majority. The EnMAP scene is predominately fitted with the sea grass bottom type. The underestimation is not linked to the sea grass bottom type, as it dominates in the shallow water regions as well, where the inversion derived the water depth quite accurately.

The last image pair displays the results for the zone 3 in Figure 4.22e and 4.22f. The HySpex signal was fitted with both bottom types sand and mussels quite equally and the scattering is similar for both bottom types. The EnMAP bottom classification is dominated by the sea grass bottom type. Here, no direct comparison is possible as the fit parameters for the bottom cover deviate.

4.4 Inversion ambiguity

The inversion yields fit parameter combinations which model the measured HySpex signal best. In order to reduce the ambiguity attached to the inversion process, the number and value range from the fit parameters is restricted. Still, small changes in the fit parameter set up can lead to quite different results. The best fit parameter combination is very difficult to assess without insitu data and ground reference. This chapter addresses the ambiguities introduced by using different fit parameter and start value combination, as well as the ambiguity of the inversion process itself.

Artefacts and parameter dependencies The horizontal stripes present predominately in the deep water regions in every HySpex and also in the EnMAP scene are caused by a faulty fit result which is then incorporated in the inversion process of the next pixel in line during the start value estimation. Therefore, the fit of the neighbouring pixel is skewed towards the faulty value. The inversion continues to derive false values until the signal can be resolved again with the chosen fit parameters. The resulting horizontal stripes are therefore artefacts of the inversion process and are expected to occur where the semi-analytical model cannot yield values which are physical plausible based on the chosen fit parameters. The difficulty is to chose the appropriate fit parameters to enable the model a physical meaningful fit and to reduce the ambiguity by reducing the number of fit parameters.
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Figure 4.22: Dominating bottom type of HySpex zones and corresponding EnMAP simulated scene. The bottom types are: coarse sand (8), light-coloured sea grass (6) and light-coloured mussels (5).
Figure 4.23: Exemplary scatter plot of HySpex and sonar water depth for outlier detection in zone 2. The colour displays the value distribution of the fit residuum (a, b) and of the fit parameters (c, d, e).
The Pearson and the Kendall correlation coefficient as defined in section 3.5 can be applied to evaluate the ability of the semi-analytical model to differentiate between different physical processes by deriving the fit parameter values independently. The interconnection of fit parameter during the inversion would yield correlated inversion results, e.g. a higher amount of CDOM would lead to a decreased water depth retrieval regardless of the true water depth. Therefore, no correlation between fit parameters is desirable for an accurate fit result. Figure 4.24 displays the Kendall correlation matrix for all fit parameters and the additional WASI parameters residuum, spectral angle and number of iterations.

All HySpex zones show a high negative correlation between both water constituents, i.e. the phytoplankton concentration and the CDOM absorption coefficient. This correlation is not so high in the EnMAP simulated scene, where the derived correlation coefficient is only slightly negative.

The second significant correlation which can be found in all HySpex zones is a positive correlation between the CDOM absorption coefficient \( \gamma \) and the residuum.

Focusing on the correlation coefficients derived for the EnMAP simulated scene on the right side of Figure 4.24 shows a recurring positive correlation between the sand bottom type and the water constituents, where the HySpex zones show negligible correlation values. Since the resemblance of the bottom cover maps between HySpex and EnMAP was already determined in section 4.3, the occurrence of positive correlation exclusively in the EnMAP scene is likely attributed to more erroneous retrieval of water constituents. The negative correlation between the water constituents is smaller in comparison to the HySpex scenes. This might indicate that the fit parameters for the water constituents can be retrieved more independently during the inversion.

The scene-dependent correlations are evasive because it is difficult to evaluate whether the correlation is caused by local effects or due to dependencies during the inversion process in WASI. The negative correlation between residuum and water depth and number of iterations and water depth found in zone 1 and 3 can be attributed to the higher reflectance magnitude of shallow waters. Shallow waters exhibit larger reflectance values, which leads to a larger residuum and therefore to a higher number of iterations. The absence of these correlations in zone 2 might be attributed to the lack of sonar measurements in shallow water areas. A negative correlation was found between the mussel and the sand bottom type in zone 3. The bottom classification failed in this zone probably due to very low reflectance values and the derived bottom values were forced to follow the sum constraint. The remaining HySpex zones show no significant correlation between the bottom types. More importantly, the correlation between the derived water depth and the scaling factor of the respective bottom type is negligible for zone 1 and 3, and reasonable small in zone 2 to indicate only a weak correlation. These findings suggest that the inversion yielded an independent bottom classification and strengthens the informative value of the derived bottom classification maps. The found correlation between bottom types and water depth is larger in the EnMAP simulated scene, which might be attributed to the fact that the sum constraint was not adjusted for the EnMAP scene. This assumption is supported by the small negative correlation between the bottom types present in all zones. Still, the derived values imply only a weak correlation.

**Simple threshold method for outlier removal**

The removal or filtering of the faulty inversion results is complicated, especially for the water constituents and bottom cover types as they cannot be easily identified as outliers. One method to filter outliers is to define a threshold for one or more fit parameters and remove the faulty pixels based on these thresholds. The bottom classification cannot be used to derive a simple threshold for outliers, as becomes evident in the Figure 4.22. The scattering of dominating sea grass pixel might be larger, but there is no obvious threshold to exclude only the outliers.

The remaining candidates for the outlier detection are the fit parameters for the water constituents, the sun glint parameter and the WASI parameters describing the goodness of fit: the residuum and the spectral angle. Figure 4.23 displays the exemplary scatter plot of the HySpex water depth and the measured sonar depth for the zone 2. The colour range represents the respective parameter values. An intuitive approach for outlier detection might be to exclude pixel with a large fit residuum or large spectral angle. Figures 4.23a and 4.23b display the scatter plots for both WASI parameters. No clear relationship between outliers and
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Figure 4.24: Kendall correlation matrix: phytoplankton concentration $C_{\text{DINO}}$, CDOM absorption $C_{\text{Y}}$, water depth $z_B$, areal fraction of bottom types sand and sea grass, sun glint $g_{dd}$, residuum $\text{Resid}$, spectral angle $S\text{Angle}$ and number of iterations $N\text{Iter}$.
the parameter values can be established, especially for the residuum. The residuum is defined as an absolute threshold, therefore HySpex pixels exhibiting a large remote sensing reflectance signal reach this threshold fast. Small residuum values were derived for all water depths. Since shallow pixels with sandy bottom exhibit large reflectance values, they also assume high residuum values, as can be seen in Figure 4.23b. The best fit was achieved in the shallow regions independent of the different zones, hence the residuum can not be used to identify outliers.

The values for the spectral angle vary for the entire water depth. While it seems that larger spectral values are associated with an overestimation and increasing scattering in the 2 to 4 m range, many outliers with low spectral values remain. Therefore, the spectral angle is not applicable for a simple threshold.

The fit parameters displayed in Figure 4.23c to 4.23e exhibit also no clear relationship between depth outlier and fit value. The assumed values are quite homogeneous and small for the CDOM absorption and the sky glint fit starting at a water depth of 3 meters.

To conclude, the simple threshold approach for outlier detection is not applicable for neither of the HySpex zones or the EnMAP scene. Different future approaches for outlier detection and filtering are discussed in chapter 5.

Variability due to model set up  The fit parameters which models the scene best in general were found by testing different fit parameter combinations for each scene systematically. The Tables B.2, B.3, B.4 and B.5 list the applied fit parameter combinations and evaluate the fit accuracy of the water depth by calculating the Pearson correlation coefficient, the MAPE and RMSE values and the slope and intercept of the linear regression.

The best inversion run (column run 8) and the worst inversion run (column run 12) for zone 1 yield diverging values for the water depth accuracy: the correlation coefficient including shallow water depths up to the averaged Secchi depth of 5.7 m assumes values from 0.31 to 0.9 and the corresponding RMSE yields values from 0.64 m to 5.82 m. The model set up of run 8 and run 12 was similar despite the large deviations in water depth accuracy. All fit parameters and constants remained unchanged except the surface effect fit parameter which should attribute the effects of sun and sky glint. Run 8 was set up with the parameter $g_{dd}$ and run 12 with the parameter $f_{dd}$.

The fluctuation of the water depth accuracy was smaller for the inversion runs applied to zone 2 and 3 as they were based of the best inversion result of zone 1. Still, the calculated correlation coefficients for the Secchi depth ranges from 0.60 to 0.82 for zone 2 and from 0.52 to 0.84 for zone 3, respectively.

This results demonstrate that the choice of fit parameters is complicated and highly influences the derived accuracy. The most care is needed when inverting regions which exhibit unfavourable conditions, like non-shallow regions with dark bottom covers and turbid water. Still, a variety of fit parameter combination were able to retrieve similar water depth accuracies for favourable conditions, as 8 out of 12 inversion runs for zone 1 derived correlation coefficients ranging from 0.73 to 0.91.
5 | Discussion

The quality of the results and the different influencing factors are discussed in following. First, the quality of the HySpex imagery and the simulated EnMAP scene are evaluated and limitations in the preprocessing steps are identified. Next, the general applicability of chosen fit parameters and inversion strategy are evaluated. Last, the the quality of the bathymetry and bottom classification maps are discussed and compared to the literature values.

5.1 Data preprocessing

The data quality of the HySpex and consequently of the EnMAP simulated scene are influenced by the environmental conditions during the acquisition, the instrument calibration and the atmospheric correction.

The HySpex imagery was acquired during variable weather conditions and the flight lines which were least impacted by clouds was chosen for the data set. Therefore, the image should not be impaired by cloud shadows to a higher degree and the image quality is therefore mostly limited by the sensor calibration and atmospheric correction steps.

Although a sophisticated characterisation and calibration of the VNIR and SWIR sensor was conducted by Lenhard et al. [2015], it could not be applied to the image data as the necessary software tool was under development during the period of the campaign. Therefore, the prior characterisation and calibration file was applied for the image data. However, the updated calibration might improve the image quality further.

The largest impact on the image quality is probably due to the atmospheric correction procedure in ATCOR. The correction was conducted manually for each flight line but not specifically adapted for water applications only. The edges of neighbouring flight stripes are clearly visible in the mosaic for the entire data set. Since the result of the surface fit parameter $g_{dd}$ resembles the flight strip boundaries (see Figures C.2 to C.4) but to a much lower extent in the simultaneously derived maps of water depth, water constituents and bottom types, it can be concluded that $g_{dd}$ compensates partly the effects of the deviating acquisition geometries of different flight stripes. Nevertheless, the remaining fit parameter results exhibit jumps at the flight stripes boundaries which impair the continuity of the fit result. Therefore, an adjusted method to correct path radiance and glint effects during the atmospheric correction might be beneficial to the image quality. The correction of glint effects in hyperspectral data is the subject of extensive research, for examples in the studies by Kay et al. [2009], Kutser et al. [2009] and Gilerson et al. [2018]. The path radiance correction also contributes to the data quality and an improved correction is researched by Ibrahim et al. [2018].

Still, the areas where reflectance of water is low with remote sensing reflectance values near of 0.5 % remain probably in the uncertainty range from the calibration and atmospheric correction. It is not easy to estimate the total uncertainty of the remote sensing reflectance, as it is composed of different uncertainties: the radiometric uncertainty which approximates the sensor noise, the radiometric error introduced during the calibration and the non-linearity of the HySpex sensor itself and the uncertainties associated with the atmospheric corrections. The radiometric uncertainty for the central pixels of the HySpex-VNIR is wavelength dependent and ranges from circa 1.1 % in the infrared to 1.8 % in the blue channels [Lenhard et al., 2015]. The uncertainty of the aerosol determination using the ATCOR-module was estimated by Pflug et al. [2015] and yielded an error of 4% which corresponds to an approximated uncertainty of 0.004 1/sr remote sensing
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reflectance. Since aerosol type and load are critical for an accurate retrieval of reflectance spectra [Gilerson et al., 2018], this uncertainty value of 0.004 remote sensing reflectance can be used as a first threshold for masking dark pixels.

To conclude, the limiting factors in the dark areas of the image, for example in zone 3, are limitations of the HySpex sensor and the associated data quality and the corresponding atmospheric correction, where the introduction of small errors result in a high relative error of the remote sensing reflectance.

The EnMAP simulated scene is composed of the HySpex flight stripes and therefore exhibits similar impairments. Since the operational EnMAP data will be provided as homogeneous scenes, the jumps present in the fit results due to the flight stripe boundaries will not occur. The inversion is expected to deliver smoother results and less impaired by glint effects.

5.2 Inversion strategy

The best choice of fit parameters largely depends on the local conditions. Although several fit parameters were tested systematically in different combinations by sensitivity analysis and inversion, no final and explicit fit parameter set can be derived which satisfies the variety of environmental conditions. The inversion of multi-temporal imagery might improve the reliability of the chosen fit parameters for water regions with similar characteristics as the Baltic Sea.

Still, the applied fit strategy and the consequential results for the best fit parameters for shallow or deep water regions described in section 4.1 provide a detailed guideline for inexperienced users. The best fit parameters for the study area are the phytoplankton concentration \( C_{\text{dino}} \), the CDOM absorption coefficient \( C_Y \), the bottom types coarse sand and bright-coloured sea grass or mussels depending on the zone and the surface parameter \( g_{dd} \). The good bathymetry results in Zone 1 and 2 underline the applicability of the fit parameters with regard to the Baltic Sea. Yet, the large divergence of fit results for the different zones presented in section 4.4 suggests that detailed fit-tuning is still necessary to obtain reliable inversion results.

5.3 Quality of derived bathymetry and bottom classification

5.3.1 Validation and bathymetry accuracy

The accuracy of the derived bathymetry maps was validated with sonar measurements which were acquired in the scope of the campaign. The comparison was conducted by excluding several sources of uncertainties: the uncertainties connected to the echosounder measurements, the impact of tidal effects since the measurements were not conducted simultaneously and the spatial re-sampling to match the resolution of the EnMAP simulated scene. The influence of these uncertainties on the measured water depths will be discussed in the following. Additionally, the derived water depths will be discussed and the derived depth accuracies will be compared to the findings of relevant remote sensing bathymetry studies.

The sonar measurement was conducted with an inflatable boat and the position was logged using a GPS instrument. The positioning error is considered to be negligible but the uncertainties of the depth measurement using the echosounder may have an significant influence. Unfortunately, the uncertainty of the system is not specified. The comparison with the official depth charts showed a maximum deviation of 21 cm. Still, it is reasonable to assume an average depth uncertainty in the centimetre magnitude.

The sonar measurements were conducted in the time frame of 4 days and therefore tidal effects can lead to a systematic error between the derived water depth and the measured water depth. All measurements were acquired during the morning hours. The systematic error is not necessarily consistent for all HySpex zones, as the sonar measurements were acquired within a time frame of circa 4 hours and the tide changes from low tide to high tide in 6 hours. The tidal range for the Baltic Sea is rather small, with values of 10 to 15 cm measured in the southern part of the study region, in Boltenhagen [Boltenhagen travel Magazin, 2014] and 5 to 10 cm in Wismar [Leibniz-Institut für Ostseeforschung Warnemünde, 2008].
5.3. QUALITY OF DERIVED BATHYMETRY AND BOTTOM CLASSIFICATION

The last major source of uncertainty is limited to the simulated EnMAP bathymetry results. Multiple sonar measurements lie inside the 30 m x 30 m EnMAP pixel. The sonar depths were simple averaged without weighting their spatial orientation which might lead to a skewed comparison. However, the averaging of several sonar measurements might reduce the uncertainties connected to the echosounding process.

The effect of the combined uncertainties is difficult to quantify. The largest influence seems to be attributed to tidal effects, although it would be rather time-consuming to extract the tidal information for each flight line and sonar measurement to apply a tidal correction for the Baltic Sea. The uncertainty attached to the sonar measurement is estimated to be within the decimetre range taking all sources of uncertainties into account. Therefore, the comparison with the HySpex water depths is also attached with an uncertainty in the decimetre range which is translated to the derived accuracy metrics.

The stability and accuracy of the water depth retrieval varies strongly for different environmental conditions. The best metrics were derived for the zone 1, which is characterised by shallow water regions with dominantly sandy bottom. The $RMSE$ for shallow water areas is 0.64 m and the corresponding $MAPE$ is 13.26 % for zone 1. In intermediate water depths ranging from depths larger than 5.7 m and smaller than 11.4 m, the $RMSE$ increases to 3.88 m with a $MAPE$ of 29.63 %. The $RMSE$ and $MAPE$ for shallow regions in zone 2 are larger, reaching values of 1.16 m and 19.34 %, although the inversion stability of zone 2 is similar to zone 1. The results for intermediate water depths are: $RMSE = 2.57$ and $MAPE = 21.10$ %

The key differences between zone 1 and 2 are the diverging depth distribution and the bottom composition: zone 2 is situated in a deeper water region and sea grass and mussels cover a larger part of the area. The comparison with zone 3, which is dominantly covered with mussels and sea grass, emphasises the importance of sandy bottom cover for an accurate water depth retrieval: The inversion in zone 3 is not stable and contaminated with artefacts. The derived $RMSE$ and $MAPE$ for sallow regions are very high with 10.16 m and 221.50 %. The failed inversion in zone 3 can be explained with the dark bottom cover and the low remote sensing reflectance. Stumpf et al. [2003] described similar issues when deriving the water depth with an empirical method using multi spectral imagery over various bottom cover types in the reef atolls located at the Hawaiian Islands. The determination failed in regions where the water exhibits a lower remote sensing reflectance than in deep water. These areas were linked to 'extremely dense algae or sea grass cover'[Stumpf et al., 2003, p. 9].

Jay and Guillaume [2014] derived the water depth applying a statistical mapping method over the French west coast using also a HySpex VNIR instrument. The $RMSE$ calculated for three sites with water depths from 4.7 m to 11.8 m was 0.54 m which is significantly lower as the derived $RMSE$ for zone 1. However, the water depths were estimated over sandy soils looking at the RGB-images [Jay and Guillaume, 2014]. The lowest $RMSE$ derived by Dekker et al. [2011] ranges from 0.91 (water depth range: 0 - 13 m) to 0.96 m (water depth range: 0 - 10 m) in a study area composed of various bottom types. In order to compare the derived $RMSE$, the different water constituents should also be taken into account. The chlorophyll concentrations measured in the study area in Dekker et al. [2011] are significantly lower compared to the Baltic Sea. The absorption coefficients for CDOM are not explicitly stated in Dekker et al. [2011] but an overall absorption coefficient was derived with values ranging from 0.02 - 2.63 m$^{-1}$. Therefore, the water compositions diverge from the Baltic Sea which should be taken into account when comparing the $RMSE$ values. Additional literature $RMSE$ are listed in Table 2.1.

The significance of the inter-comparison of $RMSE$ literature values would increase when considering only pixels which exhibit a sandy bottom type. The bottom classification is linked to the retrieval of water depth and since no bottom type ground reference data is available it is difficult to evaluate the $RMSE$ for sandy pixels only. A rough estimate is calculated based on the sand cover maps displayed in Figure 4.20, chosen the pixels with scaling factors ranging from 1-1.5 and including all water depths. The adapted $RMSE$ for zone 1 is 1.98, 1.9 m fo zone 2 and zone 3 exhibit still very large values with 11.2 m.

The $RMSE$ calculated for the zones in the EnMAP simulated scene varies from 2 m in zone 1 to 6 m in zone 3. The comparison between the $RMSE$ calculated from the bathymetry maps using either HySpex imagery or the EnMAP simulated scene yields no significant difference in zone 1, an increased error in zone 2 for the EnMAP scene and a decreased error in zone 3. The larger pixel size in the EnMAP scene averages
and therefore probably reduces the random noise which occurred in the zone 2, leading to a lower RMSE. The increase in zone 2 might be attributed to the fact that fewer uniform shallow water pixels are present in the EnMAP scene. The inversion retrieves therefore fewer correct shallow water depths and more incorrect deep water pixels, which increases the RMSE.

To conclude, the derived bathymetry accuracy is smaller compared to the relevant literature while exhibiting good correlation coefficients. This can be attributed to the different natural characteristics of the Baltic Sea and to the diverging methodology and materials. However, an outlier detection would certainly increase the derived bathymetry accuracy and enable the generation of more reliable bathymetry maps. A possible method to achieve outlier detection based on the proportion of the bottom backscatter signal to the total reflectance signal is presented in chapter 6.

### 5.3.2 Bottom type accuarcy

The bottom classification was conducted for sand and sea grass in zone 1 and 2 and for sand and mussels in zone 3. The classification was based on the spectral library derived by Schnalzer [2016] and is a baseline for the different bottom classes like sand, mussels, algae and sea grass. The resulting bottom cover maps display scaling factors which describe how large the areal fraction of the chosen bottom type has to be to fit the reflectance originating from the bottom.

The derived bottom cover maps can only be validated by comparing them with the RGB-images. The sand cover maps display reasonable results in water depths within the Secchi depth. The spatial structures of sand ripples of the study area coincide well with high scaling factors in zone 1 and 2. The sand cover map of zone 3 is dominantly contaminated by noise effects. The sea grass cover maps however cannot be validated as it is not easy to differentiate between sea grass and mussels or algae in the RGB-image.

The main limitation of the bottom classification is attributed to an accurate water depth retrieval [Dekker et al., 2011]. The choice of spectral library is also very important to derive a stable classification. Bright spectra were preferable compared to darker spectra based on the sensitivity analysis and the inversion results.

Additionally, the value range from the bottom types and their sum was not varied during the inversions. One bottom type can assume values ranging from 0 to 2 but the sum of all bottom types must be within 0.5 and 2. Therefore, the bottom classification was forced to derive values where no bottom signal should be detectable, most of all in deep and dark regions. The lower boundary of the sum definition might be set to 0 in order to derive more stable results in the deeper or optical darker parts of the image. Despite the boundary rules, the inversion results for sand and sea grass in zone 1 and 2 show no or minor correlation between the different bottom types. This underlines the capability of the inversion to derive bottom fit parameters independently from water depth and water constituents. The results for zone 3 display a negative correlation. This indicates that the inversion retrieved high values for one bottom type while forcing the other bottom type to lower values. Since the entire inversion failed in zone 3, the bottom classification does not retrieve physical meaningful values.

The bottom classification of the EnMAP scene in zone 1 and 2 shows negative correlation between the two bottom types, therefore the upper boundary should be adjusted accordingly for larger pixels.

The interpretation of the bottom classification maps was based on the averaged Secchi depth as the maximum water depth for a reliable classification. The Secchi depth itself was highly variable throughout the study area and changed quickly. Therefore, an independent indicator for reliable bottom classification is needed. The method for water depth outlier detection by Brando et al. [2009], which will be presented in chapter 6, links the detectability of the bottom signal with the outlier detection. It may offer a combined solution to derive more reliable results for depth retrieval and bottom classification.
6 | Outlook

6.1 Improved sensor characterisation and adapted atmospheric correction

The independent characterisation of the HySpex VNIR and SWIR sensor was conducted by Lenhard et al. [2015]. A newer characterisation and an improved calibration could not be applied because the necessary software tool was still under development. The software is finished by now and the complete HySpex imagery was newly calibrated. This new data set is expected to exhibit an improvement in the curve shape of the remote sensing reflectance signal, since the spectral resolution of the sensor was determined more accurately. The newly calibrated data set could be advantageous for the inversion process, especially in the VIS range. The characterisation of the bottom types and the determination of water constituents might improve significantly.

The new data set has to be corrected with the ORTHO and ATCOR module to correct geometric and atmospheric effects. The same settings for the ortho-rectification and the geometric correction can be applied to the new data set, as the acquisition geometry stays the same. However, the atmospheric corrections can be adjusted for water applications only. The ATCOR module was predominantly developed for land applications, but the change of aerosol type to maritime and the adjustment of the radiometric gain might be beneficial, especially over dark surfaces.

Due to the limited time frame of this master thesis, the geometric and atmospheric corrections of the hyperspectral data could not be applied in time.

6.2 Outlier detection

The method proposed by Brando et al. [2009] defines the substratum detectability index (SDI) as quality criterion for water depth and bottom type retrieval from hyperspectral imagery.

The calibrated and corrected imagery was inverted using the physical based semi-analytical model by [Lee et al., 1999] and the inversion-optimisation algorithm SIMPLEX Nelder and Mead [1965]. The inversion model therefore resembles the WASI method. The optimisation residuum however is defined as the combination of spectral angle and least square minimum. The contribution of the bottom to the total remote sensing signal is assessed with the SDI by comparing the modelled signal originating from the deep water \( R_s^- \) to the modelled total remote sensing signal \( R_{sh}^- \). The scene and sensor dependency of the remote sensing signal is introduced with the noise equivalent difference in reflectance \( NE\Delta r_{rsE} \). The SDI can now be defined using the terminology stated in section 3.3.1 as follows:

\[
SDI = \max \left( \frac{|R_{sh}^- - R_s^-|}{NE\Delta r_{rsE}} \right) = \max \left( \frac{|exp(-k_d \cdot z_B)[R_{r_s}^b A_2(-k_B \cdot z_B) - R_s^- A_1 \cdot exp(-k_{ulW} \cdot z_B)]|}{NE\Delta r_{rsE}} \right). \quad (6.1)
\]

The determination of \( NE\Delta r_{rsE} \) is already implemented in WASI and can be applied over dark, homogeneous water areas. Brando et al. [2009] used the Automated Local Convergence Locator (ALCL) method by Wettle et al. [2004] to derive the \( NE\Delta r_{rsE}(\lambda) \) more accurately. The method is based on the assumption that \( NE\Delta r_{rsE}(\lambda) \approx \sigma(\lambda)_{R_s^-} \), with \( \sigma(\lambda)_{R_s^-} \) being the standard deviation. The standard deviation is first calculated for a multiple values in a defined sample size \( N \times N \). By applying a linear regression to the derived \( \sigma_N \)
against the sample size $N$, the relative slope $m_{\text{rel}}$ can be calculated by dividing the derived slope $m_\sigma$ with the standard deviation of the smallest sample size $\sigma_{\text{start}}$. The relative slope is then calculated for each band $B$ and the slope for the ALCL method can be derived with

$$m_{\text{ALCL}} = \sum_{b=1}^{N_B} \frac{|m_{\text{rel},b}|}{N_B}.$$  \hspace{1cm} (6.2)

The homogeneity of the image can be assessed by comparing the $m_{\text{ALCL}}$ value for every pixel. Areas with low, homogeneous $m_{\text{ALCL}}$ values can be used to retrieve the relative slope $m_{\text{rel}}(\lambda)$ as an approximation of the noise equivalence difference in reflectance $NE\Delta r_{\text{SVE}}(\lambda)$. The selection of the sample size $N$ is based on an educated guess.

The SDI values are then used to categorise optically shallow waters, quasi-optically deep waters and optically deep waters where no substratum signal is detected. Pixels falling in the last category can not be used for bathymetry retrieval or bottom classification and are excluded from the maps. The optimization residuum can be used in combination with the SDI output to eliminate pixels which are affected by clouds. Only pixels exhibiting a small residuum and a high SDI are used to derive bathymetry maps. The $\text{RMSE}$ improves significantly after the masking based on the quality criterion: the $\text{RMSE}$ before quality control is 3.85 m which was improved to 0.95 m afterwards [Brando et al., 2009].
The aim of this master thesis was to derive the bathymetry and bottom cover of coastal areas in the German Baltic Sea by inverting airborne hyperspectral HySpex imagery and simulated EnMAP data with a semi-analytical physical model. Furthermore, the relevant fit parameters for bottom types, water constituents and surface effects were determined by applying a sensitivity analysis. The accuracy of the water depth retrieval was quantified based on in situ sonar measurements and the bottom classification was evaluated based on true-colour RGB-images.

The relevant fit parameters were determined using the sensitivity analysis and the inversions of small subsets: The relevant bottom types are coarse sand, bright sea grass and rather bright mussels. The concentration of phytoplankton and the absorption coefficient of the coloured dissolved organic matter CDOM are the relevant fit parameters for the water constituents. In addition, the surface parameter $g_{dd}$ has to be used to model the remaining influences of the remaining atmospheric signal, resulting from the different recording geometries of the individual flight strips. Additionally, the results of the sensitivity analysis showed that the mean water depth error decreases with increasing bottom reflectance. A mean relative water depth error in the range from 5 to 35 % for a water depth of 0.1 to 4 m can be expected.

The validation of the retrieved water depths was conducted for three sites which vary in their bottom cover types and exhibit different water depth distributions. The first (1) and second (2) site yield water depth estimates for the HySpex imagery with (1): up to +/- 15 % mean systematic error for water depths up to 6 m when calculating the mean water depth difference with a 50 cm binning interval and with (2): up to +/- 25 % systematic error for water depths up to 10 m. The corresponding Mean Absolute Percentage Error MAFE were derived with (1): 14 % and (2): 19 % for water depths smaller than the averaged Secchi depth of 5.7 m. The inversion of HySpex image covering the third (3) site failed probably due to the dark bottom cover. The corresponding errors of the water depths were (3): up to + 240 % for the mean error and 192 % MAPE for water depths up to 7 m, and up to the Secchi depth respectively.

The bathymetry results for the EnMAP simulated scene were evaluated for the same sites: site (1) yields systematic errors up to +/- 18 % for binning intervals of 1 m up to 6 m water depth. Site (2) exhibits a mean systematic water depth error from -45 % to 0 % up to 10 m water depth. The mean systematic error for the third site (3) is in order of + 120% for water depths up to 7 m. The corresponding MAPE for water depths up to the averaged Secchi depth are (1): 13 %, (2): 15% and (3): 100 %.

The comparison with literature values of RMSE $\sim$ 1 m for water depths up to 14 m shows that the accuracy derived in this master thesis is generally worse. However, the bottom in the study area is a mixture of sand and dark mussels/sea grass which should be addressed in the comparison - including only bright sand pixels for the calculation of the RMSE would allow for a more meaningful comparison.

The bottom classification using HySpex and simulated EnMAP imagery yielded reasonable results for sand in all study sites up to the Secchi depth. Other bottom covers including sea grass and mussels were used during the inversion but could not be verified.


## Overview of sensitivity analysis

Table A.1: Sensitivity analysis for mussels and sea grass bottom cover. The green box displays the bottom type which is fitted the most. The mean derived bottom reflectance is denoted with $R$.

Water depth simulated from 0.1 m to 4 m in 50 steps


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<th>inverse bottom type</th>
<th>initial fraction</th>
<th>mean</th>
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Table A.2: Sensitivity analysis for sand and sediment bottom cover. The green box displays the bottom type which is fitted the most. The mean derived bottom reflectance is denoted with $R$.

Water depth simulated from 0.1 m to 4 m in 50 steps


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Table A.3: Sensitivity analysis for water constituents. The green box displays the bottom type which is fitted the most, the initial values of the fit parameters are displayed in bold and italic characters.

Water depth simulated from 0.1 m to 8 m in 50 steps

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Overview of inversion runs for subset 3

Table B.1: Inversion results of subset 3 in zone 1 with measured water depths in the range from 3 to 6 m. The initial values of the fit parameters are displayed in bold and italic characters.

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<td>0.48</td>
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<td>0.246</td>
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<td>0.48</td>
<td>0.01831</td>
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<td>0.48</td>
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<td>0.48</td>
<td>0.01831</td>
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<td>-0.97</td>
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</table>
Overview of inversion results

Table B.2: Inversion results of the simulated EnMAP scene for Zone 1 to 3. The initial values of the fit parameters are displayed in bold and italic characters.

<table>
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<tr>
<th>Model parameters</th>
<th>run 1, Zone1</th>
<th>run 1, Zone2</th>
<th>run 1, Zone3</th>
<th>run 2, Zone1</th>
<th>run 2, Zone2</th>
<th>run 2, Zone3</th>
</tr>
</thead>
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<td>f[A]</td>
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<td>8</td>
<td>8</td>
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<tr>
<td>f[B]</td>
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<td>6</td>
<td>6</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>f_dss</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1.5</td>
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<td>1.5</td>
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<tr>
<td>f_dd</td>
<td>1</td>
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<td>1</td>
<td>1</td>
</tr>
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<td>0.03</td>
<td>0.03</td>
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<tr>
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<td>0.246</td>
<td>0.246</td>
<td>0.246</td>
<td>0.246</td>
<td>0.246</td>
</tr>
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<td>1.42</td>
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<td>10, analyt.</td>
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</table>

Validation

<table>
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<tr>
<th>Metric</th>
<th>run 1, Zone1</th>
<th>run 1, Zone2</th>
<th>run 1, Zone3</th>
<th>run 2, Zone1</th>
<th>run 2, Zone2</th>
<th>run 2, Zone3</th>
</tr>
</thead>
<tbody>
<tr>
<td>N(SD &lt; zB &lt; 2 xSD)</td>
<td>286</td>
<td>1030</td>
<td>153</td>
<td>286</td>
<td>1030</td>
<td>153</td>
</tr>
<tr>
<td>N(zB &lt; SD)</td>
<td>716</td>
<td>540</td>
<td>637</td>
<td>716</td>
<td>540</td>
<td>637</td>
</tr>
<tr>
<td>r: SD &lt; zB &lt; 2 x SD</td>
<td>0.94</td>
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<tr>
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<td>0.26</td>
<td>0.25</td>
<td>0.46</td>
<td>0.29</td>
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<tr>
<td>Slope: zB &lt; 2 x SD</td>
<td>1.03</td>
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<td>0.71</td>
<td>0.32</td>
<td>1.05</td>
</tr>
<tr>
<td>Intercept: zB &lt; 2 x SD [m]</td>
<td>-0.31</td>
<td>1.85</td>
<td>2.33</td>
<td>0.44</td>
<td>1.87</td>
<td>3.64</td>
</tr>
<tr>
<td>MAPE: zB &lt; SD [%]</td>
<td>12.65</td>
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<td>14.18</td>
<td>16.99</td>
<td>100.36</td>
</tr>
<tr>
<td>MAPE: SD &lt; zB &lt; 2 x SD [%]</td>
<td>31.17</td>
<td>42.28</td>
<td>72.63</td>
<td>29.88</td>
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<td>46.65</td>
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<td>RMSE: zB &lt; SD [m]</td>
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<td>0.64</td>
<td>0.84</td>
<td>6.48</td>
</tr>
<tr>
<td>RMSE: SD &lt; zB &lt; 2 x SD [m]</td>
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<td>5.92</td>
<td>3.14</td>
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</table>
Table B.3: Inversion results of the Zone 1. The initial values of the fit parameters are displayed in bold and italic characters.

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<th>Model parameters</th>
<th>run1 (low glint)</th>
<th>run2 (high glint)</th>
<th>run3 (low glint)</th>
<th>run4 (low glint)</th>
<th>run5 (low glint)</th>
<th>run6 (low glint)</th>
<th>run7 (low glint)</th>
<th>run8 (low glint)</th>
<th>run9 (low glint)</th>
<th>run10 (low glint)</th>
<th>run11 (low glint)</th>
<th>run12 (low glint)</th>
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<td>0.153</td>
<td>0.153</td>
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<td></td>
</tr>
<tr>
<td>N(SD &lt; zB &lt; 2 xSD)</td>
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<td>1627</td>
<td>1632</td>
<td>1627</td>
<td>649</td>
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<td>1627</td>
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<tr>
<td>N(zB &lt; SD)</td>
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<tr>
<td>r: zB &lt;= SD</td>
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<td>0.86</td>
<td>0.79</td>
<td>0.85</td>
<td>0.87</td>
<td>0.32</td>
<td>0.84</td>
<td>0.86</td>
<td>0.79</td>
<td>0.85</td>
<td>0.87</td>
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<tr>
<td>r: SD &lt; zB &lt; 2 x SD</td>
<td>0.15</td>
<td>-0.17</td>
<td>0.12</td>
<td>0.12</td>
<td>0.65</td>
<td>0.44</td>
<td>0.84</td>
<td>0.12</td>
<td>0.12</td>
<td>0.65</td>
<td>0.44</td>
<td>0.84</td>
</tr>
<tr>
<td>Slope: zB &lt; 2 x SD</td>
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<td>0.26</td>
<td>0.22</td>
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<tr>
<td>Intercept: zB &lt; 2 x SD [m]</td>
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<td>0.97</td>
<td>0.90</td>
<td>-2.95</td>
<td>-1.73</td>
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<td>0.97</td>
<td>0.97</td>
<td>0.90</td>
<td>-2.95</td>
</tr>
<tr>
<td>MAPE: zB &lt;= SD [%]</td>
<td>48.71</td>
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<td>30.80</td>
<td>34.15</td>
<td>17.26</td>
<td>26.48</td>
<td>48.71</td>
<td>34.38</td>
<td>30.80</td>
<td>34.15</td>
<td>17.26</td>
<td>26.48</td>
</tr>
<tr>
<td>MAPE: SD &lt; zB &lt; 2 x SD [%]</td>
<td>124.11</td>
<td>72.10</td>
<td>63.30</td>
<td>67.75</td>
<td>30.39</td>
<td>132.32</td>
<td>124.11</td>
<td>72.10</td>
<td>63.30</td>
<td>67.75</td>
<td>30.39</td>
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<td>1.38</td>
<td>6.77</td>
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<td>1.21</td>
<td>1.34</td>
<td>0.72</td>
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</tr>
<tr>
<td>RMSE: SD &lt; zB &lt; 2 x SD [m]</td>
<td>20.78</td>
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<td>3.03</td>
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<td>6.75</td>
<td>5.94</td>
<td>6.31</td>
<td>3.03</td>
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</tr>
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</table>

Validation

<table>
<thead>
<tr>
<th>Model parameters</th>
<th>run7 (low glint)</th>
<th>run8 (low glint)</th>
<th>run9 (low glint)</th>
<th>run10 (low glint)</th>
<th>run11 (low glint)</th>
<th>run12 (low glint)</th>
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</thead>
<tbody>
<tr>
<td>f[A]</td>
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<td>8</td>
<td>8</td>
<td>8</td>
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<td>f[B]</td>
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<td>f_dd</td>
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<tr>
<td>C_Y</td>
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<td>0.25</td>
<td>0.25</td>
<td>0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>C_dino</td>
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<td>1.42</td>
<td>1.42</td>
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<td>1.42</td>
<td>1.42</td>
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<td>zB</td>
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<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

Validation

| N(SD < zB < 2 xSD) | 1627           | 1627           | 1627           | 1627           | 1627           | 1627           |
| N(zB<SD)          | 5163           | 5163           | 5163           | 5163           | 5163           | 5163           |
| r: zB <= SD      | 0.91            | 0.90            | 0.73            | 0.66            | 0.34            | 0.31            |
| r: SD < zB < 2 x SD | 0.33            | 0.36            | 0.32            | 0.68            | 0.19            | 0.08            |
| Slope: zB < 2 x SD | 1.29            | 1.15            | 2.55            | 6.33            | 4.13            | 3.14            |
| Intercept: zB < 2 x SD [m] | -0.56           | -0.35           | -3.63           | -12.75          | -7.06           | -4.16           |
| MAPE: zB <= SD [%] | 14.02           | 13.26           | 13.51           | 12.47           | 27.00           | 40.00           |
| MAPE: SD < zB < 2 x SD [%] | 35.32           | 29.63           | 134.22          | 395.63          | 271.21          | 221.22          |
| RMSE: zB <= SD [m] | 0.66            | 0.64            | 1.25            | 1.56            | 4.81            | 5.82            |
| RMSE: SD < zB < 2 x SD [m] | 5.01            | 3.88            | 17.91           | 45.17           | 56.23           | 56.93           |
Table B.4: Inversion results of the Zone 2. The initial values of the fit parameters are displayed in bold and italic characters.

| labels A, B: 1: clay, 2: loamy sand, 3: sandy loam, 4: dark mussels, 5: light mussels, 6: bright sea grass, 7: dark sea grass, 8: coarse sand, 9: fine sand; Secchi depth (SD) = 5.7 m |
|---|---|---|---|---|---|---|---|
| Model parameters | run1 (low glint) | run2 (high glint) | run3 (low glint) | run4 (low glint) | run5 (low glint) | run6 (low glint) |
| f[A] | 8 | 8 | 8 | 8 | 8 | 8 |
| f[B] | 6 | 6 | 6 | 5 |  |  |
| f_ds | 1 | 1 | 1.5 | 1.5 | 1 | 1 |
| f_z | 1 | 1 | 1 | 1 | 1 | 1 |
| g_dd | 0.03 | 0.03 | 0.03 | 0.03 |  |  |
| C_Y | 0.246 | 0.246 | 0.246 | 0.246 | 0.246 | 0.246 |
| S | 0.0183 | 0.0183 | 0.0183 | 0.0183 | 0.0183 | 0.0183 |
| C_dino | 1.42 | 1.42 | 1.42 | 1.42 | 1.42 | 1.42 |
| zB | 2 | 2 | 2 | 2 | 5 | 5 |

Validation

| N(SD < zB < 2 x SD) | 5109 | 5109 | 5109 | 5109 | 5109 | 5109 |
| N(zB < SD) | 2727 | 2727 | 2727 | 2727 | 2727 | 2727 |
| r: zB <= SD | 0.60 | 0.65 | 0.82 | 0.83 | 0.73 | 0.90 |
| r: SD < zB < 2 x SD | 0.05 | -0.02 | 0.28 | 0.28 | 0.26 | 0.29 |
| Slope: zB < 2 x SD | 0.15 | 0.13 | 0.71 | 0.66 | 0.71 | 0.52 |
| Intercept: zB < 2 x SD [m] | 1.17 | 1.21 | 1.38 | 1.86 | 2.13 | 2.06 |
| MAPE: zB <= SD [%] | 46.77 | 48.25 | 19.34 | 24.03 | 35.7 | 18.97 |
| MAPE: SD < zB < 2 x SD [%] | 71.57 | 72.73 | 21.10 | 20.47 | 20.65 | 26.82 |
| RMSE: zB <= SD [m] | 2.05 | 2.04 | 1.17 | 1.17 | 1.95 | 0.78 |
| RMSE: SD < zB < 2 x SD [m] | 6.94 | 7.07 | 2.57 | 2.49 | 2.47 | 2.96 |

Table B.5: Inversion results of the Zone 3. The initial values of the fit parameters are displayed in bold and italic characters.

| labels A, B: 1: clay, 2: loamy sand, 3: sandy loam, 4: dark mussels, 5: light mussels, 6: bright sea grass, 7: dark sea grass, 8: coarse sand, 9: fine sand; Secchi depth (SD) = 5.7 m |
|---|---|---|---|---|---|---|---|
| Model parameters | run1 (low glint) | run2 (high glint) | run3 (low glint) | run4 (low glint) |
| f[A] | 8 | 8 | 8 | 8 |
| f[B] | 6 | 6 | 6 | 5 |
| f_ds | 1 | 1 | 1.5 | 1 |
| f_z | 1 | 1 | 1 | 1 |
| g_dd | 0.03 | 0.03 | 0.03 | 0.03 |
| C_Y | 0.246 | 0.246 | 0.246 | 0.246 |
| S | 0.0183 | 0.0183 | 0.0183 | 0.0183 |
| C_dino | 1.42 | 1.42 | 1.42 | 1.42 |
| zB | 2 | 2 | 2 | 10 |

Validation

| N(SD < zB < 2 x SD) | 887 | 659 | 887 | 887 | 887 |
| N(zB < SD) | 5338 | 664 | 5338 | 5338 | 5338 |
| r: zB <= SD | 0.67 | 0.84 | 0.53 | 0.58 | 0.54 | 0.52 |
| r: SD < zB < 2 x SD | 0.19 | 0.01 | 0.13 | 0.13 | 0.36 | 0.19 |
| Slope: zB < 2 x SD | 0.34 | 0.26 | 2.44 | 2.55 | 1.86 | 3.70 |
| Intercept: zB < 2 x SD [m] | 0.31 | 0.85 | 1.88 | 1.38 | 4.21 | -1.68 |
| MAPE: zB <= SD [%] | 56.35 | 47.54 | 197.45 | 192.32 | 221.50 | 206.73 |
| MAPE: SD < zB < 2 x SD [%] | 62.82 | 63.67 | 171.28 | 173.46 | 123.47 | 255.84 |
| RMSE: zB <= SD [m] | 2.28 | 1.42 | 10.35 | 10.16 | 9.81 | 13.71 |
| RMSE: SD < zB < 2 x SD [m] | 5.36 | 5.83 | 16.20 | 16.18 | 10.75 | 24.49 |
C  |  Overview of fit parameter maps

Figure C.1: Overview of inversion results for the EnMAP simulated scene.
Figure C.2: Overview of inversion results for zone 1.
Figure C.3: Overview of inversion results for zone 2.
Figure C.4: Overview of inversion results for zone 3.
D | Declaration of originality

I hereby declare that I have written my thesis independently and that I have not used any other sources and aids than those indicated.

Munich, December 11, 2018, Martina Wenzl