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Uncertainties associated with in situ high-frequency long-term observations of suspended particulate matter concentration using optical and acoustic sensors

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Abstract
Measurement of suspended particulate matter concentration (SPMC) spanning long time and large geographical scales became a matter of growing importance in the last decades. On many places worldwide complex observations platforms have been installed to capture temporal and spatial variability over scales ranging from cm (turbulent regimes) to whole basins. Long-term in-situ measurements of SPMC involve in general one or several optical and acoustical sensors of similar or different technical specifications and, as the ground truth reference, gravimetric measurements of filtered water samples. The estimation of SPMC by optical and acoustical surrogates generally results from the combination of a number of technically independent calibration measurements and regression or inverse models. Direct or indirect measurements of SPMC are inherently associated with a number of uncertainties along the whole operation chain from laboratory work over system problems during mostly unsupervised deployment to convert the observed continuous proxy values of optical and acoustical signals to SPMC.
Controlling uncertainties will become an important issue when observation comprises systems of sensors spanning large spatial and temporal scales in order to detect trends in the data with unambiguous statistical significance, to separate anthropogenic impact from natural variations or to evaluate numerical models over a broad ensemble of different conditions using validated field data.
The aim of the study is to present and discuss potentials and limitations related with the use of optical and acoustical backscatter sensors, to describe challenges and uncertainties associated with long-term observations of SPMC and to formulate recommendations as a basis to acquire quality-assured SPMC data sets. On the basis of examples the main sources of errors as well as means to quantify and reduce the uncertainties associated with SPMC measurements are illustrated.
1. Introduction

Water clarity is an important parameter to understand marine ecosystems and is mainly controlled by suspended particulate matter concentration (SPMC). Data on water clarity collected during the last century, indicate significant local and global environmental changes due to human activities and climate change (Capuzzo et al., 2015; van Maren et al., 2016). The conclusions from these studies are, however, hampered by the often poor quality of the historical data and the very low time resolution of the measurements with regard to the high dynamic nature of the systems in which the data have been collected. In view of documenting current and future trends, high quality measurements spanning long time, large geographical scales and high time resolutions, became a matter of growing importance (Henson, 2014). To detect variabilities in SPMC, networks of observations platforms have been installed worldwide using optical and acoustical sensors as well as sensors that give additional information on shape and size of the SPM, and as the ground truth reference, gravimetric measurements of filtered water samples (e.g. Butman et al., 1979; Grabemann and Krause, 1989; Fettweis et al., 1998; Guézennec et al., 1999; Ganju and Schoelhamer, 2006; Krivtsov et al., 2008; Badewien et al., 2009; Cartwright et al., 2009; Gray and Gartner, 2009; Palinkas et al., 2010; Garel and Ferreira, 2011; Nauw et al., 2014; Anastasiou et al., 2015; Fettweis and Baeye, 2015; Jalón-Rojas et al., 2015; van der Hout et al., 2015; Many et al., 2016; Baschek et al., 2017; Druine et al., 2018). The infrastructure on which the sensors are attached includes fixed (piles, benthic landers, tripods) and moving platforms (vessels, gliders, AUV, ROV) or a combination of both, and the SPMC may cover the whole range from oligotrophic to hyperturbid conditions.

Long-term and high frequency data series of SPMC are typically collected indirectly with unsupervised sensors that measure either the optical beam attenuation as a percentage of light transmission (Moody et al., 1987; Spinrad et al., 1989; Agrawal and Pottsmith, 2000), the back- or sidescatter intensity of light in volt or factory calibrated turbidity units, or the backscatter of sound in counts or volt (Thorne and Hanes, 2002; Downing, 2006; Rai and Kumar, 2015). The combination of different sensors measuring in environments with high temporal and spatial variations implicitly demands adapted pre- and post-measurement procedures in order to obtain homogenous data sets. Conversion of the sensor output to physical units (e.g. mass or volume concentration of particles) results from laboratory and field calibrations, and data post processing procedures. The whole procedure requires direct measurements in the laboratory using calibration against standard turbidity solutions and in the field using SPM mass concentrations determined through filtration of water samples. The way the sensor output is transformed to SPMC (in g/l) depends further on the modelling techniques used to relate sensor output to SPMC and is further complicated by the significant variability of the inherent...
optical (IOP) and acoustical properties (IAP) of the SPM (e.g. Boss et al., 2009a; Sahin et al., 2017). To guarantee the quality and repeatability, not only the laboratory procedures, but also the measuring process, from the planning to the measurements itself and the post processing of the data, needs to be documented (Lane et al., 2000; Waldmann et al., 2010; Bolanos et al., 2011; Gil et al., 2016).

Direct or indirect measurements of SPMC are inherently associated with a number of uncertainties along the whole operational chain from planning over laboratory work, to system problems during mostly unsupervised deployment and to converting the observed continuous proxy values of optical and acoustic signals to SPMC. Guidelines for good practice for fluvial sediment transport measurements can be found in e.g. Rasmussen et al. (2009). However, limited information exists in guidelines or standards that can be applied to long term observation programs of SPMC in marine and estuarine environments. Recent literature highlights only part of uncertainties or problems related to the use of optical and acoustical sensors (Rai and Kumar, 2015; Rymszewicz et al., 2017). The aim of this study goes further as it discusses potentials, limitations and problems of present practices related to the use of optical and acoustical sensors in long-term deployments and formulates recommendations that may form a basis to acquire best quality-assured SPMC data sets. Other uncertainties or biases in the observation, which are e.g. related to the representativeness of the measuring location within the regional context, the interactions of the measuring infrastructure with the environment, are not part of this study.
2. Methods for long-term in situ SPM concentration measurements

Long-term in situ measurements of SPMC in coastal seas and estuaries involve in general one or several optical and acoustical sensors of similar or different technical specifications and, as the ground truth reference, gravimetric measurements of filtered water samples. The combination of indirect and reference measurements require two main calibration steps (sensor and model parameter calibration) at different moments during the workflow in order to extract reliable and homogeneous SPMC. These calibration steps are essential to be able to relate possible changes in calibration constants (sensor and model parameter) to sensor degradation or to natural variability in SPM inherent properties.

2.1 Terminology

The terminology related to calibration, turbidity or sensors is not unambiguously used, e.g. distinction between the two calibration steps is not mentioned explicitly and turbidity units are often wrongly used. A well-defined terminology is important to obtain consistent and uniform sensor SPMC in long term (and other) measurements, where multiple sensors are used together (in parallel and in succession).

Sensor calibration refers to the comparison of the output signal of an optical or acoustical sensor against a standard in the laboratory (e.g. Thorne et al., 1991; Downing, 2006). For turbidity this is usually formazine or an alternative standard (AMCO clear, StablCal), while for acoustical backscatter intensity a solution of standard spheres with a given size distribution, concentration and at a given distance from the transducer is used. Acoustic sensor calibration is not commonly applied for long-term measurements due to practical difficulties in setting up a laboratory device. Sensor calibration results in converting the sensor output to various turbidity units (see below) or decibels (dB). During long-term field operations the sensor calibration constants against a standard may alter, due to e.g. changes in battery supply, (bio-)fouling, degradation of the measuring window or of the sensor. Any of these changes in the sensor calibration constants are inherent to the sensors and not to the environment and must if possible be corrected.

Model parameter calibration is the result of a regression of inverse optimization with sensor signals after sensor calibration, ideally from the undisturbed environment, as input and corresponding to the real SPMC as output. This type of calibration is well distinguished from sensor calibration as it relies on natural particles (in contrast with formazine or an alternative standard that consist of artificial polymeric particles, see Downing, 2005) and has to be carried out regularly or each time when the SPM inherent properties change significantly. If the sensors have been well-calibrated then any changes in model calibration constants are caused by
changes in SPM inherent properties. Variabilities in these properties affect the relation between real SPMC and sensor signal.

Sample SPMC is the SPMC obtained from filtration and gravimetric measurements of water samples. As the real SPMC cannot be measured by any direct method we will use the sample SPMC as our reference SPMC, as it is by a lesser degree influenced by the inherent particle properties of the SPM (Neukermans et al., 2012a; Röttgers et al., 2014).

Sensor SPMC is a surrogate obtained by an acoustical or optical backscatter sensors or other type of sensors. Depending on the methods different surrogates of SPMC are obtained. In case of long-term measurements different sensor SPMCs are often obtained that represents surrogates or proxies that are not necessarily the same (e.g. Rai and Kumar, 2015; Rymiszewicz et al., 2017).

Turbidity refers to the optical water cloudiness caused by suspended particles and dissolved substances, which scatter and absorb light (Downing, 2005; Ziegler, 2003; Gray and Gartner, 2009). Turbidity has not a SI unit, is not uniquely defined and differs according to the applied protocols. It is thus an arbitrary unit that is incomparable to measurements taken at other times and places or with different turbidity meters, which diminishes the comparability of turbidity data for scientific purposes (Downing, 2006). The ISO Method 7027 (ISO, 1999) and the American EPA Method 180.1 (EPA, 1993) estimate turbidity in formazine Nephelometric Units (FNU) or Nephelometric Turbidity Units (NTU), respectively. For these two methods, the optical sensor to be used is a nephelometer that must measure side-scattered light, i.e. at 90°, with a difference between the two norms regarding the source light wavelength. The definition of turbidity following the EPA method, using a tungsten light source with color temperature between 2200-3000K and detector and filter system with spectral peak response between 400nm and 600nm, is poorly determined. The strengths of the ISO method include the use of a stable monochromatic near infrared light source of 860nm with low absorbance interference with samples, which is critical in reducing the impact of particulate and coloured dissolved organic matter absorption and in having a low stray light (Sadar, 1999). Sensors designed according to the EPA specification may thus give very different results for the same sample, whereas the ISO definition of turbidity does provide a better basis for the comparability of measurements (Barter and Deas, 2003, Nechad et al., 2009) and is therefore recommended when no legal regulations require other protocols.

Both protocols refer to a formazine-equivalent turbidity value. In case an alternative standard is used, then it should be explicitly stated that turbidity refers to the alternative standard-equivalent NU or TU. The unit of the formazine (or of another) standard is generally –for historical reasons - given in NTU although the solution is established following the ISO or EPA
protocol. In an ISO-compliant formazine solution of 1000 "NTU" an ISO-compliant side-scattering sensor will measure 1000 FNU, whereas an EPA-compliant side-scattering sensor will measure another value in NTU. The difference between FNU and NTU is mainly due to the spectral range of lights that are emitted by the instruments, e.g. in waters with particles highly absorbing in the blue-green range, EPA-compliant instrument measures lower turbidity values than an ISO-compliant instrument.

Optical Backscatter Sensors (OBS) measure the particle backscattering of light at different angles of detection (120°-165°, or even including side and forward scattering depending on the type of sensor); although highly correlated, the turbidity measured by an OBS and a Nephelometer is not necessarily the same; e.g. Nechad et al. (2016) report a large variability in the relationship between in situ side- and back-scattering coefficients in the lower turbidity range (<20 FNU) and a convergence with increasing turbidity. Turbidity from backscatter devices should be expressed in Formazine Backscatter Units (FBU) for the near IR (830-890nm) light (ISO Method 7027) and Backscatter Turbidity Units (BTU) for the EPA Method 180.1 (Dogliotti et al., 2016; Nechad et. al, 2016). Often FTU (Formazine Turbidity Unit) or NTU are used as unit without specifying how the instrument measures the sample (side, back or forward scattering) or which protocol it follows (ISO or EPA). By adapting the correct units the confusion on protocol or scattering angle can be avoided.

**2.2 Inherent properties of SPM**

SPM is a mixture of clay to sand sized particles in suspension that consists of varying amounts of minerals from physico-chemical (e.g. clay minerals, quartz, feldspar) and biogenic origin (e.g. calcite, aragonite, opal), living (bacteria, phyto- and zooplankton) and non-living organic matter (fecal and pseudo-fecal pellets, detritus and its decomposed products from microbial activity such as mucus, exopolymers), and particles from human origin (microplastics), see Table 1 and Figure 1. Particles are considered in suspension as long as they do not form an interconnected matrix of bonds that prevents their mobility; this corresponds to a concentration that is below the gelling point (McAnally et al., 2007). The lower limit in concentration corresponds to the detection limit of the instrumentation or sampling; the upper limit is theoretically just below the gelling point when the particles are so close together that settling is substantially hindered and a two-layer stratified flow with a distinct density interface remains (Ross and Mehta, 1989; Winterwerp and van Kesteren, 2004). Practically the upper limit depends on the sensor specifications and on the difficulties to measure in the very near-bed layer where these highly concentrated layers are found. For many sensors, the upper limit is O(10g/l), far below the gelling point concentration O(50g/l).
Depending on the seafloor composition (cohesive and non-cohesive sediments), the vicinity of sediment sources, the hydrodynamics, the measuring height above the bed and biological activity, the composition of the SPM may change with time. Sand grains are generally limited to the near-bed layer (bed-load), while fine-grained sediments can be found along the water column. The fine particles, such as clay minerals, other charged particles and polymers in suspension may become attached to each other (floculation) to form fragile structures or flocs with compositions, sizes, densities, and structural complexities that vary as a function of turbulence, chemical environment (salinity) and bio-chemical composition (e.g. Eisma, 1986; Dyer and Manning, 1999; Droppo et al., 2005; Fettweis and Lee, 2017). While the size of the building particles of flocs is of the order of a few µm, fully developed flocs may grow up to a few hundreds of µm or more; larger flocs have generally higher water content, higher organic content and lower density.

Changes in the concentration and the composition of the SPM influence the optical and acoustical properties and if not calibrated for these conditions also the sensor SPMC. Further to changes in composition the SPMC is generally higher in the estuarine and nearshore areas (10 mg/l up to O(1-10 g/l), due to resuspension and erosion of bed material, river inputs, coastal erosion, and estuarine circulation, than in more offshore deeper areas of the continental shelf (<10 mg/l). As a consequence, SPM properties and concentration fluctuate on a broad range of temporal and spatial scales with different magnitudes and exhibit substantial gradients along estuaries and with distance from the coast (Fettweis et al., 2006; Becker et al., 2013; Maerz et al., 2016; Many et al., 2016).

2.3 Sensors used to obtain long-term SPMC time series

2.3.1 Sensitivity of optical sensors to inherent particle properties

Various measurements of IOPs, which do not change with changing light field in water, are used as surrogate to SPMC. Optical sensors rely on propensity of SPM to interact with light (at a given wavelength λ) through absorption a(λ) and scattering b(λ). For long-term measurements, the attenuation or the scattering at a given angle are mainly used to obtain the SPMC surrogates. Details on the optical properties of particles can be found e.g. in the Ocean Optics Web Book (2018). Available sensors can differ in wavelength and backscattering angle. Particles backscattering of light, b_b(λ), is theoretically calculated as the integration of volume scattering function (VSF), denoted by β(λ,θ) [m⁻¹ sr⁻¹] with θ the scattering direction, covering all backward directions. Boss and Pegau (2001) and Berthon et al. (2007) showed that b_b is highly correlated to β at angles between 120°-140°. A good approximation for b_b(λ) is to be estimated from b_b(λ,140°), while Chami et al. (2006) found that the increase of β at θ > 150° can significantly impact the backscattering. The backscattering of particles at large wavelengths
(λ>700nm) gives the best estimations for SPMC (Downing, 2006; Boss et al., 2009a). The effect of absorption by particles and coloured dissolved organic matter is high at shorter wavelengths (Yentsch, 1962) and can impact (back)scattering or turbidity estimation by sensors that use light source emitting at short wavelengths, as was highlighted by Sutherland et al. (2000) and Downing (2005). In more turbid waters, high particles absorption impacts more the estimation of backscattering coefficient even at longer wavelengths and should be properly corrected for (Doxaran et al., 2016). As mentioned above, ISO Method 7027 (ISO, 1999) and EPA Method 180.1 (EPA, 1993) estimate turbidity \( T \) in Formazine Nephelometric Units (FNU) or Nephelometric Turbidity units (NTU), respectively, such as \( T = \frac{\beta(90^\circ)}{\beta^F(90^\circ)} \) where \( \beta^F(90^\circ) \) is the VSF at 90\(^{\circ}\) of a unit of formazine, at prescribed wavelength. However, other types of optical sensors, such as backscatter sensors, are widely used to measure turbidity and hence to estimate SPMC. In terms of sensor calibration, i.e. based on successive dilution of a standard solution, this does not cause problems as the sensor output will be compared, and then associated, to the standard solution that can be expressed in a turbidity unit. This calibration must then be used for quality control and to ensure the stability of the intrinsic sensor performance, and possible drifts induced by electronic failure or damages on optical windows that may induce maintenance and repair. The main issue comes when these instruments measure turbidity in situ or from natural water samples as IOPs (i.e. scattering efficiency \( K \)), in that case the VSF are dependent on particles shape (Slade et al., 2013), particles size and density, refractive index (Mishchenko et al., 2002; Boss et al., 2004), and colour (Sutherland et al., 2000; Hatcher et al., 2000).

Generally, \( b(\lambda) = K(\lambda,r)N(r)\pi r^2 \), where \( K \) is the scattering efficiency factor for non-absorbing particles, \( N \) the number density of particles, and \( r \) the particle radius. For spherical particles \( SPMC = \frac{4}{3}N\rho\pi r^3 \), where \( \rho \) is the dry density (i.e. particle mass divided by the particle volume), resulting in a ratio of turbidity to SPMC that is inversely proportional to the particle radius and density (Sutherland et al., 2000):

\[
\frac{b}{\rho r} = \frac{3}{2}k(\lambda,r)\frac{SPMC}{\rho r}
\]  

(1)

The SPM dry density (proportional to the excess density) can, depending on the particle composition, be anywhere in between the range of well below 100 kg m\(^{-3}\) for the organic flocs and up to 2650 kg m\(^{-3}\) or more for the individual mineral particles. In case the SPM consists of flocs the variations in density and size can be very large, with the densest flocs having the smallest size and vice versa. The consequence of this is that the dependence of \( b \) on \( \rho r \) is weaker than its dependence on \( 1/r \) (Bowers et al., 2009) but can still be significant (Gibbs, 1985; Babin et al., 2003; Baker and Lavalle, 1984). This demonstrates that a change in the
composition of particles and/or their shape, size and density affects the turbidity measured by a side- and backscatter sensor (e.g. Binding et al., 2005; Neukermans et al., 20012b; Zhang et al., 2014; Druine et al., 2018), but also indicates that the model parameter calibration of optical backscatter instruments using a single optical property (backscattering coefficient or beam attenuation) against sample SPMC is often successful over a wide range of particle sizes (Boss et al., 2009b; Bowers et al., 2017).

2.3.2 Sensitivity of acoustic sensors to particle properties
Acoustics devices commonly used in coastal areas, i.e. ADVs or ADCPs are primarily designed for current velocity measurement. Similarly to optical devices, the emitted acoustic wave, at a given frequency, interacts with particles in suspension while propagating in the medium and are backscattered to the receivers (Thorne and Hanes, 2002). The recorded volume backscattering strength ($S_v$, in dB) is a proxy of the SPM concentration, but is also strongly modulated by SPM features such as size, density and shape, depending on the acoustic wavelength. Originally used in sandy environments (Sheng and Hay, 1988; Thorne and Hanes, 2002), these devices are now routinely deployed in fine sediments environments (e.g. Gartner, 2004; Hoitink and Hoekstra, 2005; Tessier et al., 2008; Sahin et al., 2013). The sonar equation (Urick, 1975) is commonly used to relate $S_v$ (in dB) and SPMC concentration, including acoustic signal correction for geometry compensation, spherical spreading, and water and particle attenuation:

$$\frac{S}{N} = SL - 20log_{10}(\varphi R^2) - 2\int_0^R(a_w(r) + \alpha_s(r))dr + S_v + 10log_{10}\left(\frac{\sigma R^2 ws}{\rho s v_s}\right)$$

(2)

and

$$S_v = 10log_{10}\left(\frac{SPMC \sigma}{\rho_s v_s}\right)$$

(3)

where $S/N$ is the signal to noise ratio (dB) received by the device. After Gostiaux and Van Haren (2010), Mullison (2017) specifies the values of $S/N$ in function of the raw echo readings (in counts) of the ADCP devices. $SL$ is the source level (dB); $R$ is the along-beam distance from transducers, $a_w$ and $\alpha_s$ respectively the water and sediment attenuation, $\varphi$ the angular aperture; $ws$ the cell size and $\psi$ the near field correction. $\sigma$, $\rho_s$ and $v_s$ are particle features: backscattering cross section, particle dry density and volume respectively.

Similarly than optical devices, the relationship between the acoustic backscatter and SPMC strongly depends on the nature, size, density and shape of the particles, either flocs or grains, both for the estimation of the particle attenuation and for the calculation of the backscattering cross section (Fugate and Friedrichs, 2002; Ha et al., 2009; Salehi and Strom, 2011; Rouhnia et al., 2014), achieved using theoretical acoustic models (Stanton, 1998; Thorne and Hanes, 2002; Thorne et al., 2014). However, contrary to optical devices, the sensor calibration is not routinely
(often never) operated due to the difficulty to access requested laboratory facilities. Hence this step is often skipped and quality check is based on comparison with other in situ sensors or SPMC samples.

2.3.3 Conversion of acoustical and optical sensor output to SPMC

The relationship between OBS or nephelometer signal and SPMC is almost linear as long as the sensor is not deployed in highly concentrated waters (Downing, 2006), and the simplest model is a linear regression model. The same holds for single point acoustical sensors (ADV) or for the first bin of a profiling acoustical sensor, where the target volume is very close to the sensors. As far as SPMC are lower than several g/l, a direct empirical relationship can be built such as

$$\log_{10}(SPMC) = S_v$$

where $$S_v$$ can be related to the signal/noise ratio (Fugate and Friederichs, 2002; Voulgaris and Meyers, 2004; Verney et al., 2007; Ha et al., 2009; Salehi and Strom, 2011).

For profiling acoustic sensors the sonar equation should be considered to correct for the signal loss along the acoustic path. The conversion factor from counts to dB, as commonly used in acoustics, is typically provided by the manufacturer. Close to the transducer, the acoustic signal has to be corrected for near-field effects (Downing et al., 1994) and for ringing effects that may affect the first bins, in particular when blank distance is set too small by in the configuration parameters. Corresponding data cannot be corrected and should be discarded (Muste et al., 2006). A formulation for the water absorption coefficient was proposed by e.g. François and Garrison (1982a, 1982b) and later simplified by Ainslie and McColm (1998), who showed that their result did not differ from the original equation more than the accuracy error. The sonar equation yields the so-called water-corrected backscatter, which is a property of the suspension at all locations along the acoustic path. Subsequent processing depends on the SPMC. In case of moderately turbid environment, i.e. lower than 100mg/l, sound attenuation by SPM is usually neglected as it is one or two orders of magnitude lower than the water absorption coefficient (Ha et al., 2011). SPMC is then either determined by applying an appropriate calibration, similar to single point optical sensors, or by a theoretical acoustic model. In the latter case, physical properties of the transducer and of the SPM must be exactly known, which are rarely available. If SPMC exceeds 100mg/l, sediment absorption should be considered. While the calibration is performed to calculate SPMC profiles, these are in turn required correcting backscatter for sediment attenuation. This is solved by iterative methods (Thorne et al., 1994; Holdaway et al., 1999). A critical point is that the sediment absorption coefficient is assumed to be known a-priori, which is somewhat contradicting. The actual calibration is correcting for unknown backscattering properties of particles in suspension, while these are implicitly assumed to be known calculating the sediment absorption coefficient (Becker et al., 2013). This technique is efficient but requires assumption or knowledge about SPM characteristics (size, density) and is
based on the choice of an acoustic model adapted to the observed SPM, and may in some specific case exponentially propagate uncertainties and fail to estimate SPMC.

When sediment attenuation must be accounted for, theoretical acoustic model must be built, simulating the physical interactions between particles and the acoustic signal (Sheng and Hay, 1988, Medwin and Clay, 1998). These models were originally designed for sand particles and hence considering particles in suspension as rigid spheres (Thorne and Hanes, 2002). They fail to represent low density aggregated SPM, and a first model derived from works by Stanton (1998) could be applied. Recent developments achieved to adapt a hybrid acoustic model for flocs, through a transition between quasi-rigid primary particles and floc-like fluid-elastic spheres (McDonald et al., 2013, Thorne et al., 2014). Differences between models mainly appear in the methodology to calculate the total scattering and backscattering cross section as well as the compressibility of flocs and their ability to interact with sound. For more details, see Thorne et al. (2014). This hybrid model was successfully applied by Sahin et al. (2017) to an estuarine environment with SPMC larger than 1g/l.

2.4 Existing international guidelines and standards

In the European context the only guidelines exist for OSPAR’s Joint Assessment and Monitoring Programme (JAMP), see JAMP (2012). They refer to the ICES TIMES report by Yeats and Brügmann (1990) that deals with the collection methods of water samples. The Trilateral Monitoring and Assessment Program for the Wadden Sea (TMAP) mentions suspended matter concentration as a supporting, not mandatory parameter in their handbook on nutrients, see TMAP (2009). The handbook explicitly refers to the corresponding guidelines of JAMP. HELCOM (2015) also treats SPMC as a co-factor in water analysis and again keeps its determination by filtration according to ISO (1997) and includes as an indirect measure for SPMC, the Secchi depth. ICES itself stipulates only guidelines for data formats.

In a global framework, the IOC-EU-BSH-NOAA-(WDC-A) International Workshop on Oceanographic Biological and Chemical Data Management dealt with a number of biogeochemical bulk parameters, but does not contain SPMC in the variable list. GOOS so far does not present best practice manuals. For the ARGO program QC manuals for bio-Argo particle backscattering measurements are yet in development (Schmechtig et al., 2015), the main purpose of these measurements is the use of the backscattering coefficient as proxy for POC concentration (IOCCG, 2011); which will possibly limit the usefulness of such QC systems to coastal seas and estuaries. NOAA is responsible for numerous monitoring programs along the US coasts, but does not provide standards for SPMC measurements in official documents. In some technical reports, however, the methods to obtain SPMC are described, always using gravimetric analyses of water samples (e.g. Pait et al., 2015).
For the large-scale integrated ocean and coastal ocean observatories, such as IOOS in the United States (https://www.ioos.us/) and IMOS in Australia (http://www.imos.org.au/), no guidelines for best practice of SPMC measurements are put forward. SPMC is not part of operational real-time observation, but at least in the case of IMOS, SPMC data sets based on water samples are regularly created at reference stations (e.g. Lynch et al., 2008). The U.S. Geological Survey provides a number of documents comprising guidelines for the sampling (Edwards and Glysson, 1999), for the lab analysis of the samples (Matthes et al., 1992; Shreve and Downs, 2005), for the proper layout and operation of field stations and sensors to meet accuracy and precision requirements (Wagner et al., 2006), and how to compute time series of SPMC and their related loads using proper statistical regression models between turbidity and sample SPMC and evaluating their outcomes (Rasmussen et al., 2009). The latter was expanded for acoustical backscatter measurements (Topping and Wright, 2016). These guidelines were developed for measurements in rivers, but many of them can be transferred to estuaries and coastal seas in a straight forward way, except that ones need to take into account that the conditions in estuarine and coastal ocean waters differ in two major aspects. Firstly, the field stations are generally more remotely located from the landside and much harder to access and to maintain. Secondly, the SPM exhibit much higher variability on texture and composition. Fluvial SPM consists predominantly of mineral matter with generally minor changes in particle size and composition, except during high river runoff, when particle size may significantly change. Estuarine and marine SPM on the other hand exhibits significant inherent variability in composition, cohesiveness and size, which increases the occurrence of uncontrolled uncertainties, the need for additional instrumentation (see Table 2) and the number of model parameter calibrations to perform.
3. Sources of uncertainties

Uncertainties, as described in Ramsey and Ellison (2007) and ISO (2008; 2017), hamper data quality and may arise from mal-functioning of sensors (3.1), the environment influencing the sensors without changes in SPMC (3.2), SPMC sample collection and analysis (3.3), modelling of sensor output to sample SPMC (3.4), the variability of the model that relates sample and sensor (3.5), and additional uncertainties arising from human error and uncontrolled environmental boundary conditions (3.6).

3.1 Sensor related uncertainties

Sensor related uncertainties occur if the sensor output changes over time unrelated to changes in inherent particle properties or SPMC. Concerning optical backscatter sensors this is caused by variations in voltage supply, changes in the transmittance of the window that is the interface between the sensor and the water or other degradations. Concerning acoustical backscatter sensors the main sensor related uncertainty is related to battery power. The reason that no other sensor related uncertainties are documented is due to the limited availability of facilities to test acoustic sensors in a lab, and that in contrast to optical sensor, no standards and norms exists so far to test and calibrate acoustical backscatter sensors. Other uncertainties may arise from the drift of the internal clock of the sensor or the data logger in particular in case of long term monitoring.

3.1.1 Drift of a sensor with time

Optical sensors are subject to gradual decreasing transmittance of the sensor window during deployment due to damages caused by the collision of particles. Therefore the factory calibration parameters should be used with care and be checked regularly. One of the authors of this study reported the result of a lab re-calibration of 11 Seapoint turbidity sensors after intense and occasional usage during several years. Optical inspection of the sensors did not indicated any damage of the transmission and detection windows. The average slope between factory calibration and formazine recalibration agreed within 1%, but the individual slopes showed descrepancies up to ±30% with a standard deviation of 15%. Figure 2 shows a comparison between an OBS3+ factory calibration and a sensor calibration obtained after 329 and 421 days highly turbid (SPMC > 1g/l) sea water. Using the factory calibration constants without recalibration would indicate an apparent increase of the turbidity. Any of these changes in the calibration constants are inherent to the sensors itself and the need of recalibration has to be specified by the user based on the required precision.

Variations in voltage supply result in a drift, which is unrelated to variations in SPMC or inherent particle properties. In clear water the output of e.g. an OBS3+ will be a minimum voltage, increasing to a maximum voltage at the maximum turbidity range. The sensor needs to...
be fed by a constant minimum voltage in order to give good data. Lower voltage supply results in an apparent decrease in turbidity. Figure 3a shows an OBS3+ in low (0-2000 BU) and high (0-4000 BU) range that has been fed with different input voltages while measuring in a standard of 2000 Amco-Clear®-equivalent BU. For an input voltage of more than 6 V the low range registers a constant value of 5.1 V (saturation), while the high range registers about half of it (2.5 V). If the supplied voltage decreases, the signal registered by the OBS3+ decreases as well. An example of a time series collected with a corrupted and a well-functioning sensor is illustrated in Figure 3b. Due to an insufficient voltage supply the recorded SPMC signal was on average about 90% lower than it should be. After sensor calibration with lower voltage supply the data could be corrected. Battery power affects also acoustical backscatter sensors (Tessier et al., 2008). From the registered battery voltage during the deployment the emitted power can be converted into the correction factor $P_{dbw}$ calculated as $P_{dbw} = 10 \log(P^2/R)$, with R the electrical resistance. If only one of the transducers of profiling acoustical sensors supplies more or less power than the others, then this can be corrected using the other transducers (Tessier, 2006).

3.1.2. Sensitivity of sensors

Some optical backscatter sensors, such as an OBS3+, are dual range sensors having both a low- and a high-range output. The two measuring ranges increase the resolution of the measurements, but each output is more accurate when its designed turbidity range matches its calibrated range. The RMS error between high and low range output depends on the turbidity, e.g. for an averaged turbidity around 20 the low range (500 BU) recordings during a tidal cycles differed by about 2% with the high range ones (2000 BU). When increasing the ranges (low: 1000 BU, high 4000 BU) then the relative difference increased to 24%. The optimal range is to be chosen according to the expected range of turbidity values in the field.

3.1.3 Inter-sensor variabilities

The aim of multi-sensor calibration is to generate a reliable model parameter calibration to estimate SPMC at long-term monitoring stations by repeated field surveys and to record variabilities caused by the use of similar types of sensors. Figure 4 shows the result of a simultaneous calibration of three OBS3+ sensors during a tidal cycle. The RMSE between the three OBS3+ sensors, which have been calibrated against the same sample SPMC, was 2.6% for 1 Hz sampling and 2% for an averaging over 60s. The difference between sensor outputs is changing during the course of the measurements. This points to small-scale variations in the SPMC (sensor are located about 50 cm from each other) and to different sensitivities of the individual sensors. These examples presented strengthen the necessity of sensor calibration (difficult to achieve for profiling acoustic sensors) and model calibration for each sensor separately.
### 3.2 Environmental related uncertainties

Environmental related uncertainties occur when the acoustic or optical backscatter sensor output changes over time unrelated to changes in inherent particle properties or SPMC or when the sensor measures outside its designated range. The former occurs when the signal is attenuated by biofouling or the occurrence of air bubbles. The latter occurs, e.g. in case of an OBS, when the emitted light beam is strongly attenuated and backscattered light decreases with increasing sediment concentration, resulting in an ambiguous interpretation of the signal (Downing, 2006; Sottolichio et al., 2011).

#### 3.2.1 Biofouling

Biofouling or other type of fouling can limit the accuracy and quality of long-term SPMC measurements within a week, depending on the season and the environment. Biofouling occurs in four phases starting with the development of an organic film, followed by primary and secondary micro colonizers and finally tertiary colonizers attach to the microfouling film (Abarzua and Jakubowski, 1995). The impact of these different phases on the recorded signal remains difficult to estimate and can result in a temporary or permanent increase of the backscattered signal due to additional reflection or a decrease due to attenuation (Kerr et al., 1998; Delauney et al., 2010). Increase of the backscattered signal can also be caused by plant or artificial (e.g. fishnet) filaments trapped by the measuring infrastructure and constantly or ephemerally influencing the detection volume. There are several methods and reasons to protect the sensors against biofouling (Ridd and Larcombe, 1994; Manov et al., 2004; Whelan and Regan, 2006). The most obvious reason is to obtain good quality data. Another one is that the fouling development on the whole measuring infrastructure can disturb the properties of the study site. For example, the growth of epi-fauna on the infrastructure may influence the measurements as they trap, accumulate and temporarily release SPM (Baeye and Fettweis, 2015). Effectively biofouling results in a gradual and continuous drift of the signal over time together with an apparent decrease in sensitivity (Dolphin et al., 2000; Downing, 2006).

Permanent biofouling events will gradually change the backscatter intensity and can only be corrected if a non affected reference sensor is at hand. The reference sensor can be single beam acoustic or optical backscatter sensor or a not-affected beam of an acoustic profiler. The onset of a change in the SPMC signal due to biofouling is difficult to identify and therefore should be based on the hypothesis that the observed changes cannot anymore be explained by known physical behaviour of SPMC variations.

Figure 5 is an example of epi-fauna (barnacles) growing on an OBS that resulted in an increase of backscatter intensity until saturation and thus an overestimation of the SPMC. The timing of biofouling was estimated at the point where the ratio of the affected sensor to a non affected
one started to increase monotonically. Biofouling has also been observed on moored up-ward
looking ADCPs. A straightforward identification of these events is possible by computing the
maximum backscatter ratio (Jourdin et al., 2014). In absence of biofouling the ratio will have
values close to the sensor noise (typically 1 dB). A drop of up to 10 dB has been observed in
ADCP moorings deployed off the French coast (Jourdin et al., 2014), while in an ADCP mooring
off the Belgian coast a gradual drop of more than 20 dB in backscatter strength have been
recorded. A value of 10 dB leads to under-estimation of the suspended sediment concentration
by one order of magnitude, over the entire acoustic profile. If only one beam of an ADCP is
affected by biofouling, this can be corrected by applying the median function to all beams as
explained in Jourdin et al. (2014). Figures 6 is an example of permanent biofouling resulting in a
gradually decrease of the backscatter strength during the mooring, while in Figure 7 shows
episodic biofouling events.

3.2.2. Saturation and ambiguity problems

SPMC in the field may vary from several mg/l to a few g/l. At these ranges, the OBS output
increases with SPMC, and the gain setting is adjusted by the manufacturer for an optimized
sensitivity at the expected concentrations in the field. However for too high turbidity values,
saturation occur and the OBS output will show a plateau as illustrated in Figure 5. The individual
setting of certain probes can be adjusted (see §3.1.2) to broaden the range of SPMC before
saturation, but this operation is limited for water where concentration exceeds several g/l.
For many OBS probes, beyond the saturation range, the output signal decreases with increasing
concentration as was first observed in the field by Kineke and Stenberg (1992). They attributed
this trend to the partial blockage of the emitted beam by highly concentrated suspensions, the
reduction of the scattering volume relative to the area of detection. Figure 8 shows typical bell-
shaped backscatters curve, meaning that a given OBS output can correspond to two possible
SPMC values. The two values that can be obtained (i.e. the up and over response) depend on
the sensitivity of the individual sensor. This bell-shaped response can be particularly useful
when measuring very high concentrations (Sottolichio et al., 2011). Because of this ambiguity,
the determination of SPMC in highly concentrated waters (>4 g/l) is not always possible. A
correction is possible in case of vertical profiles, where SPMC is continuously increasing
downward (Kineke and Sternberg, 1992). However, this does not help in case of time series,
obtained by one probe at fixed height above the bed. The use of a second probe above the
other e.g. could help to solve the ambiguity of one of the two probes. Acoustic backscattering
sensors show the same type of response than optical probes, and the ambiguity issue apply
thus also to acoustic devices, such as single point ADV sensors (Ha et al., 2009; Sottolichio et al.,
2011).
3.2.3 Effects of air/gas bubbles

Due to the high acoustic impedance or the very different refractive indices between gas and water, the volumetric backscattering strength measured by acoustical sensors or the scattering efficiency measured by an optical sensor is sensitive to the presence of air or gas microbubbles (1 to 500 µm in radius) in water. These bubbles are mainly generated at the sea surface by wave breaking or white-capping (e.g. Schwendeman and Thomson, 2015) and as a consequence the backscattering strength also depends on the sea state in addition to SPMC (e.g. Klein, 2003; Downing, 2006; Puleo et al., 2006). The finest bubble population of typical size less than 50 µm in radius penetrates deeper within the water column where it can remain in near-equilibrium suspension (e.g. Randolph et al., 2014). Outside the surf zone, bubbles can be carried down in form of plumes or patches by convergent fronts or wind-induced down-welling to depths up to 30 m (Wang et al., 2016). The vertical distribution of wave bubbles decays exponentially with depth resulting in a similar decrease of the backscattering strength at lengths scales of 0.5 to 5 m (Wang et al., 2016). Expressed in decibels the backscattering intensity displays a linear decrease with depth (e.g. Wang et al., 2011) and this property together with measurements of the wind speed ($U_{10}$) and wave height in parallel can be used to discard parts of profiles affected by wave bubbles, see the example in Jourdin et al. (2014).

3.3 Sample related uncertainties

Sample related uncertainties occur during collection and analysis of the sample SPMC, i.e. the filtering and weighing. A diversity of methods and equipment are used to collect water samples, such as Niskin bottles, Go-Flow bottles and stand-alone or on-board sea water pump or suction systems. The bottles attached on a CTD system (vertical), Rosette (vertical) or other profiling frame (horizontal), or the intake for the pump system should be in the vicinity of the sensors, which are deployed for model calibration. To our knowledge no conclusive investigations have been published so far on sampling devices for fine-grained (cohesive) SPM in turbulent coastal and estuarine waters.

Standard protocols for dry mass SPMC determination (Strickland and Parsons, 1968; Pearlman et al. 1995) and additional procedures to partition SPMC into its organic and inorganic content (e.g. loss on ignition, element analysis) are straightforward: They include filtering a specific volume through a pre-weighed filters, washing of sample filters to remove salt, drying, and weighing of the filter to determine the dry mass of the SPMC. In early years, paper filters were used; later membrane filters (Banse et al., 1963) have been in use, while nowadays often glass-fibre filters (type GF/F or GF/C) are used. A critical step in the determination of SPMC is the removal of the salt in filters from seawater samples (Banse et al., 1963). Additional uncertainties are related to the determination of the dry mass and filter volume and the
amount of structural water in minerals (Barillé-Boyer et al., 2003), see Stavn et al. (2009) for an overview. Most uncertainties are related to a constant mass offset (salt, weight and volumetric determination) and are, hence, relatively small when enough mass of particulates (several milligram) is collected on the filter. The collection of a sufficient mass is easy to achieve in turbid nearshore or estuarine waters dominated by mineral material, but more difficult in low turbid organic-rich waters or e.g. during a Phaeocystis bloom. In the latter case the gelatinous algal colonies may clog the filter before enough material is collected and prevent the removal of the salt. In cases where the sample mass on the filter is not very high, errors due to salt are significant (Banse et al., 1963; Stavn et al., 2009; Röttgers et al., 2014). In cases where the sample is turbid (>100 mg/l), the main uncertainty is often caused by the difficulty to homogenize the sample prior to subsampling and filtration (Fettweis 2008). Methodological improvements include the optimization of the filtration volume and cleaning of the filter margin after the funnel is removed (Neukermans et al., 2012a); the correction of the salt mass bias using procedural control filters (Stavn et al., 2009), the filling of the filter margin with salt-free water before filtration and the determination of a SPMC free of the salt-bias using a set of different sample volumes (Röttgers et al., 2014).

The uncertainty in sample SPMC decreases with increasing SPMC as shown for a data set of about 2500 sample SPMC from the Belgian nearshore obtained with the method of triplicates with the same volume using GF/C filters. The uncertainty (expressed as the RMSE of the triplicates divided by the mean value) is highest (8.5%) for sample SPMC lower than 5 mg/l and decreases with increasing SPMC to 6.7% (<10 mg/l), 3.5% (10-50 mg/l) and 2.1% (>100 mg/l). This error corresponds to the uncertainty introduced if only one replica was used instead of three replicas. In case of triplicates the error is limited by excluding sample SPMC with a RMSE exceeding a threshold value. The need of subsamples with different volumes versus subsamples with the same volume has been checked from samples collected in three stations with different turbidity in the southern North Sea. The estimated slope, i.e. the SPMC, has an uncertainty that can be higher than 1 mg/l (>30%) for clearer waters (SPMC about 3 mg/l) and then it drops to about 0.3 mg/l for SPMC of about 11 mg/l (3%) or 25 mg/l (1%). Using the method with the same volume, the uncertainty is about 0.3 mg/l (10%) for the clearest sample, about 0.4 mg/l (4%) for SPMC around 11 mg/l and about 0.8 mg/l (3%) for SPMC of around 25 mg/l. The relative difference between the estimated SPMC using this method and the different volume method (applied three times, and averaged) is about 11% for clear waters, 6% and 4% for higher levels of turbidity. One should consider that the uncertainty (standard deviation) of the SPMC through averaging of triplicates with the same volume is not the same uncertainty as that obtained via the slope determination using the different volume method. The latter includes a
random and a systematic error due to the offset by salt, while the same volume method
provides only a measurement error. The systematic error is not detected in the same volume
method, which explains the apparent lower uncertainty of this method, especially at low SPMC
as compared to the different volume method. The method with different volumes is more
accurate, the latter holds especially in low SPMC waters, where the effect of salt is important
(Röttgers et al., 2014).

3.4 Relating sensor output to sample SPMC

Modelling techniques establish a statistical relationship between turbidity or acoustical
backscatter intensities and reference SPMC data. This relationship is applied to convert the
time-series of turbidity or acoustical backscattered signal into SPMC. The reference SPMC
should preferably be the sample SPMC (ISO, 2014), however, for acoustic devices such as an
ADCP a calibration against in situ water samples is challenging, as samples are often difficult to
collect next to the profiling sensor and as the property of the SPM may change over the water
column. For these cases the SPMC derived from optical sensors is often used as reference
SPMC. This procedure will add additional uncertainty to the model.

The first part of this section (§3.4.1 and §3.4.2) deals with a purely technical aspect, i.e. the
biases involved with the choice of the linear regression model. The second part addresses
uncertainties that are caused by systematic changes of the particle IOPs or IAPs that will result
in varying proportional factors between the detected signal and SPMC that are not detected
during the generally short calibration periods (§ 3.4.3). Very often, these cover only a tidal cycle
in the pre- or post-measurement phases using, e.g. a rosette with Niskin bottles or a water
pump. A general bias in the model parameter calibration relation may be caused by the spatio-
temporal mismatch between the sample and the sensor, by local changes in the turbulence and
floc size caused by the sampling device or by the calibration period that is not necessarily
representative for the whole unsupervised time series. The latter may result from changes of
the particle properties within the same area, due to variable meteorological and hydrodynamic
conditions that lead to the resuspension of particles of different size, composition, shape and
dynamic modification of the particle characteristics due to flocculation processes. The third part
(§3.4.4) deals with the inconsistencies between parallel optical and acoustical data that are
caused by the uncorrelated and random variations in the IOPs and IAPs.

3.4.1 Modelling techniques for optical and acoustical sensors

The relationship between optical sensor output to SPMC or the acoustic backscatter to the
$10\log_{10}(\text{SPMC})$ can be modelled using a linear model (see §2.3). The model can be applied to
the linear domain or the log-log transformed domain (the latter only for turbidity data). Mostly,
after quality checks of the data, linear regression finds optimal regression parameters by
minimization of the squared differences between the values of the dependent variable and the regression line (X² method, further called LSQ). In general, however, different options for the linear regression method can be considered that lead to different values in the regression parameters for the same data set and different levels of predictability of SPMC from optical turbidity or acoustic backscatter intensity.

The first option is the choice of the independent (explanatory) and dependent (response) variable. As one finally wants SPMC as a function of turbidity, mostly SPMC is used as dependent variable. On the other hand, as turbidity depends on SPMC and not vice versa, causality requires turbidity as dependent variable to compute SPMC from turbidity using the inverse of the regression. As another option, one may regard both SPMC and turbidity as only statistically, but not causal dependent on each other. This situation may be adequate for cases where water sampling locations and turbidity detections volumes differ by typically more than the coherence lengths of the SPMC in the observation area. Then the minimization of the difference between data and regression line should take place perpendicularly to the regression line solving an Eigenvalue problem. This method leads to symmetric results no matter whether SPMC or turbidity is the dependent or independent variable.

In most real data sets, the assumptions for linear regressions, i.e. the residuals are normally distributed, linear along the zero line, and of constant variance across the range of the dependent variable (homoscedastic), are not met (e.g. Gilbert, 1987). Often, the data sets may contain outliers, i.e. data that do not follow the pattern of the other observations beyond the tails of normal distributions. Then, ordinary least-squares fitting can have undesired sensitivities both in best model parameter or confidence interval estimations. In this study, two examples of robust fitting are contrasted with ordinary least-squares, i.e. the Theil-Sen estimator, a non-parametric method that determines model slope m by the median of the slopes through all data pairs of data points and then computes the intercept from the median of all data pair residuals \( y_i - mx_i \) (Wilcox, 2001), and the “iteratively reweighted least squares” method (further called Robust) in which the weighted sum of the absolute differences between the regression line and the dependent data is minimized with the weight being the inverse of the differences in the former iteration step (Press et al., 1989).

To overcome the problems with data heteroscedasticity, \( \log_{10} \) - transformations of the variables can be applied, a decision that should be based on the examination of the model residuals (Helsel and Hirsch, 2002). This transformation has also the advantage that the distribution of data along the independent variable is more homogeneous as there is very often a bias in the coastal water sample data sets towards lower SPMC. The re-transformation of the regression line into the original units introduces a bias that arises as the regression estimates are...
computed from means in log units unequal to the mean in original units. Helsel and Hirsch (2002) recommend the usage of the non-parametric “smearing” estimator introduced by Duan (1983) as bias correction factor (BCF) with $n$ the number of samples, and $e_i$ the residual of sample $i$ in log-units. This BCF is not symmetric when using the Eigenvalue regression in the log space as SPMC and turbidity have different units.

An example of the different methods and the exchange of dependent and independent variables is shown in Figure 9 for the calibration of an OBS against sample SPMC. The next example shows the direct calibration of an ADCP (1 MHz Nortek AWAC) against sample SPMC in a moderately turbid environment (<100 mg/l) is shown in Figure 10. The direct calibration with sample SPMC was performed for the surface and bottom samples separately as they originate from different population of particles in suspension, i.e. surface plume and bottom resuspension. The data are from a coastal observatory located at the mouth of the Seine estuary and consists of a bottom station equipped with an ADCP and a Wetlabs NTUSB optical backscatter sensor (Wetlab OBS) and a surface buoy measuring turbidity with a similar Wetlab NTUSB sensor. Seasonal field campaigns are conducted each year to collect surface and bottom water samples and perform CTD and turbidity vertical profiles (OBS3+ sensor).

In Figure 11 the model calibration of two acoustic sensors (3 MHz Sontek ADP with series number M284 and M947) is shown using the OBS-derived SPMC as the reference SPMC. The data is from a one year time series in 2013 collected in the turbid Belgian nearshore area at about 2 m above the bed (Fettweis et al., 2016). Both acoustic sensors have measured about half of the period at a burst rate of 15 minutes and all the available OBS and ADP data pairs have been used for the model calibration (M284: 12280; M947: 14923). The OBS sensors have been calibrated twice during the period against sample SPMC. The model calibration (M284: $R^2=0.4$; M947: $R^2=0.6$) shows strong scatter in the data and thus a high uncertainty in the acoustic derived $10\log_{10}(SPMC)$, which is even much higher when data are re-transformend to SPM. Other studies report similar and higher (up to 0.8) ranges of $R^2$ (Fugate and Friedrichs, 2002; Gartner 2004; Dufois et al., 2014). The difference between OBS and ADCP estimates of SPMC during a 1 week deployment in San Fransisco Bay was 8% to 10% relative to OBS range and about 35% to 40% relative to OBS mean (Gartner, 2004).

3.4.2 Uncertainties due to the choice of the linear regression model

To estimate the uncertainties introduced by the choice of a specific regression method, we applied fifteen different combinations of regression methods to eleven data sets using the three minimisation schemes plus the Theil-Sen estimator, exchanging turbidity and SPMC as
independent variable and taking the data with and without log_{10} -transformations. The data sets consist of pairs of sample SPMC and turbidity collected at various location with Hach nephelometers (North Sea, English Channel, Mediterranean Sea, French Guiana coast, Gironde estuary, Rio de la Plata) and Seapoint sensors (Wadden Sea, North Sea, Oosterschelde estuary, Weser estuary). The variability of the resulting regressions increases considerably with decreasing $R^2$ of the data set. In Figure 12 the percentage range of slopes (maximum – minimum) of the regression functions as SPMC=f(Turbidity) is computed for the not-transformed (i.e. linear scale) data for different values of the normalized turbidities defined as

$$Turb_{Norm} = (Turb - \langle Turb \rangle )/std(Turb)$$

where $\langle \rangle$ means the average and std the standard deviation of the turbidities in each data set.

The spread of slopes increases significantly with decreasing $R^2$ from about 0% for $R^2$=1, to 10% for $R^2$=0.93 and 30% for $R^2$=0.60 at $Turb_{Norm}$=2 (typically the 95% percentile of the turbidities).

At the center of the turbidities ($Turb_{Norm}$=0) the spread of slopes is close to zero, as expected.

For cases, where the calibration data represent only a limited range of the totally observed turbidities in the time series, the spread at higher values of turbidity should also be taken into account, e.g. at $Turb_{Norm}$=8 the percentage spread of slopes amounts to more than 50%.

Figure 12 also displays slopes and intercepts of linear regression (Eigenvalues method) to the percentage slope spread versus $R^2$. Slopes and intercepts can be closely fitted by exponentials and yields the following formula for the percentage slope spread ($S\%$) as a function of $R^2$ and $Turb_{Norm}$:

$$S\% = (140 \cdot e^{-0.35 \cdot Turb_{Norm}-135} < R^2 > + 140(1-e^{-0.44 \cdot Turb_{Norm}}) - 5$$

This formula predicts the percentage spreading within 5% for an $R^2$ of 0.91 and can be used to estimate the uncertainties involved with the choice of the regression method applied based only on $R^2$ and dependent on the value of $Turb_{Norm}$ for any data set.

To investigate how the type of regression method relates to the mean of all (7) linear scaled data regressions, we averaged the percentage spreading of each regression method over all data sets as a function of $Turb_{Norm}$ and displayed it with respect to the mean of all regressions (Figure 13). The deviation of all methods from their mean are nearly zero at $Turb_{Norm}$=0, diverge sharply towards negative $Turb_{Norm}$ up to +- 50% at $Turb_{Norm}$=-1 (average 10% percentile of the turbidities), and increase again towards higher $Turb_{Norm}$ to a plateau, that depends both of the $R^2$ of the data set and the regression method. For data sets with $R^2$>0.90, this plateau remains below $\pm$ 5 percent for all regression methods, but raises to nearly +-20% for data sets with $R^2$<0.75. Here, the regression methods differentiate distinctively from each other, see Figure 13. The LSQ method with turbidity as dependent variable and SPMC
computed from the inverse of the regression, exceeds the mean regression by +20%, whereas
the Eigenvalue and inverse robust fit regression still remain close to + 5%. All inverse
regressions have a positive bias with respect to the mean, whereas the regressions with SPMC
as dependent variable have a negative bias of the same amount. Hence averaging the direct
and the inverse regressions of one method equals the mean regression.

Within the range of the calibration data (\(T_{\text{norm}}\) between 0 and 1) the percentage spreading
remains below 10% with \(R^2 > 0.6\). At the lower range end of the calibration data (\(T_{\text{norm}} < -0.5\))
the relative uncertainties rapidly diverge (Figure 13). The situation is quite different for the regressions performed with \(\log_{10}\)-transformed data. The slope of the regression may deviate from 1, resulting in a non-linear power function after re-
transformation. This may result in quite large percentage spreading’s at high \(T_{\text{norm}}\), see
Figure 13. For data sets with \(R^2 < 0.75\), the spreading exceeds more than ±50% at \(T_{\text{norm}} = 8\)
with no signs to reach a plateau limit at higher \(T_{\text{norm}}\). For \(R^2 > 0.9\), the percentage spreading
is much lower with ±20% at most and reaching the plateau at \(T_{\text{norm}} = 6\). This value still is
four times higher than for the regressions with not transformed data. Within the calibration
data range the uncertainties are still higher by a factor of 2 compared to the not transformed
cases, but at the lower end of the turbidities they are more or less identical as all regressions
are forced to cross the origin point.

Of course, the results shown here are valid for any data set independent of the meaning of the
variables. This means that the uncertainties involved with the model calibration of acoustical
backscatter data against an OBS derived \(10\log_{10}(\text{SPMC})\) are much larger as the examples in
Figure 10 and 11 show, where the \(R^2\) is 0.4 and 0.6 respectively. The situation is even
aggravated after raising the data to the power of 10, where the uncertainties will increase
accordingly and likely exceed 100 %.

3.4.3 Natural variabilities in SPM inherent optical and acoustical properties

Variabilities in IOPs may occur between different geographical areas or within a same
measuring location. The former is illustrated in Figure 14, where the relation between sample
SPMC and Seapoint turbidity is shown for different areas in the North Sea. The spreading in the
data is caused by variabilities in inherent particle properties between the areas. Additional
causes of the differences are inter-sensor variabilities and uncertainties due to the sampling
and filtration protocols. The latter are thought to be of lesser importance as the differences in
slope of the regression lines (German Bight: 1.05 and Oosterschelde estuary: 2.34) is larger than
these additional uncertainties. Local variation in the IOPs have to be considered when turbidity
data are compiled on regional scales as a basis for SPMC mappings, as in the e.g. for coastal
observatories that deliver time series of optical turbidities at different locations.
Intra-tidal variabilities in IOPs at a same location have been observed at various locations. Figure 15a shows that the specific backscatter ratio (i.e. turbidity divided by sample SPMC) is oscillating with the tides (Becherer et al., 2016). The magnitude and the tidal signal of the ratio nearly persisted after the storm even though sample SPMC at maximum currents increased threefold. With respect to the tidal mean this would result in a systematic over- and underestimation of the SPMC by 60% over the tidal cycle. The data indicate that the product of particle density and radius is four times smaller at slack water than at maximum currents. This may be largely assigned to the organic content of the particles that increases with the specific backscatter ratio (Figure 15b). Variation in the specific backscatter ratio may also occur on seasonal time scales as observed in Liverpool Bay (Jafar-Sidik et al., 2017). These variations are caused by the seasonality of the primary production and turbulence regime and have changed the ratio by a factor 2.

Another example shows intra-tidal variations in acoustical and optical inherent particle properties due to occurrence of mixed particles (i.e. sand and mud) in suspension at a muddy and sandy bed site located in the main tidal channel of a brackish marsh in the Scheldt estuary (Schwarz et al., 2017). The optical sensor was calibrated with sample SPMC and the optical derived SPMC was subsequently used to calibrate the acoustic backscatter sensor. The muddy bed site shows a strong correlation in contrast with the sandy bed site between acoustical and optical backscatter during the two tidal cycles (Figure 16). These observations indicate constant particle properties during a tide at the muddy site and changing particle properties at the sandy site, indicating that the SPM at the muddy site consists mostly of muddy flocs resuspended from the bed, while at the sandy site sand grains with diameters comparable to those of flocs are eroded into suspension at high flow velocities. Their intermittent abundance will lead to changes in the IOP's of the SPM due to their higher specific density, i.e. the increase of \( r_{p} \) will lower the ratio of turbidity to sample SPMC (see §2.3.1, eq. 1). A storm event recorded at an observation pole in the Elbe river (Baschek et al., 2017, Kappenberg et al., 2018), discloses a further example of significant changes in this ratio due to sand grains entrained into the water column. The ratio of optical turbidity to SPMC derived from water samples taken hourly over a period of 12 hours before, during and after the storm varied from 0.4 during the moderate wind phases to 0.12 just after the peak of the wind speed (Figure 17). Grain-size analysis of the samples revealed a significant increase of mainly sand around the 90 \( \mu \text{m} \) fraction. As a consequence, optical turbidity remained in the range of average tidal variability during the storm, whereas sample SPMC exceeded this by a factor of five. Similar observations have been made at other locations where mixed sediments and/or strong changing current and wave conditions caused sandy material or particle with other erosion characteristics to be
resuspended up to the detection volumes of the acoustic and optical sensors (see e.g. Fugate and Friedrichs, 2002; Fettweis et al., 2012).
The examples demonstrated that in-situ calibration with samples are necessary at all representative locations and phases of the local hydrodynamical and biogeochemical conditions to take the varying composition of the suspended particles into account.

3.4.4 Uncertainty between optical and acoustical derived SPMC

A comparison of the modelled SPMC was performed from different optical and acoustical sensors, based on the data from the mouth of the Seine estuary (§ 3.4.1 and Figure 10). The same sample SPMC was used to build models for a moored Wetlabs OBS, a profiling OBS3+ and a moored ADCP (1MHz Nortek AWAC) and the modelled optical derived SPMC was further used as reference SPMC to build a model for the moored ADCP in order to estimate and compare model performance and associated uncertainties (Figure 18). Results show that the optical sensors have highest accuracy against sample SPMC (OBS3+: 10%, Wetlab OBS: 40%) and that the acoustical derived SPMC compare well with the OBS3+ profiles for the period where both sensors have been calibrated against sample SPMC. In the same figure the acoustic derived SPMC is compared with the SPMC time series derived from the Wetlabs OBS’s, thus for periods that are not covered by the field campaigns dedicated for calibration. The optical and acoustic derived SPMC values significantly differ, the ADCP underestimating large optical derived SPMC and overestimating the lower ones. The acoustic sensor has the larger uncertainty at lowest (400% for SPMC < 5 mg/l) and highest values; in the mid range the uncertainty is about 100% (5 mg/l < SPMC < 10mg/l) and below 50% (SPMC <75 mg/l). The results also show that the error of the reference SPMC propagates into the uncertainty of the acoustic derived SPMC, as can be seen when comparing the ADCP derived SPMC from Wetlabs OBS (20-150%) and OBS3+ (20-50%).

High uncertainties between acoustic and OBS derived SPMC have been observed in the data from the Belgian nearshore (§ 3.4.1 and Figure 11), see Figure 19. The normalized RMSE associated with the regression model varies between 100-500% (mean regression is 170%) for the M284 ADP and 90-140% (mean regression is 90%) for the M947 ADP. The uncertainty is lowest in the mid range SPMC (100-1000 mg/l), with normalized RMSE between 50-70% (M284) and 45-60% (M947) for the best regression models and higher for the lower and higher SPMC values.

Both examples indicate that the differences between acoustic and optic derived SPMC can be very large and that these uncertainties increase when long time series are used for calibration. These differences are probably caused by variabilities in inherent acoustical and optical properties of the SPM that occurred over time scales longer than the sampling surveys, by
differences in built-in sensor technology or due to time-delay between sensor measurements and sample time. In order to improve the correlation, the inherent acoustic and optical properties of the particles should be incorporated into the model calibrations.

3.5 Additional uncertainties

So far aspects of human interference in the operation chain of long-term measurements and in the deployments have been neglected. These includes errors directly caused by the human variability that influence the outcome of the measurements or by the effects of human activities not related to the operational chain that have an impact on the SPMC.

3.5.1 Human error

As everyone does also the people involved in the operation chain of long-term measurements make errors. These human errors may cover a broad range of failures related to human malfunction. Humans interfere during the maintenance, the sensor and model parameter calibration and the collection of sample SPMC. The errors are mistakes that may result in the not strictly following of the protocol, or simply by bumbling errors, such as mismeasures, miscalculations, mislabelling, malfunctioning of sensors or instruments. Maintenance, water sampling and filtering or sensor exchange often take place under tough sea state conditions and under time pressure that may result in stress, fatigue and reduced mental awareness. Under such conditions it can be difficult to strictly obey protocols and to identify and document, if any, possible deviations and mistakes in an appropriate way. Further many of the errors are often only detected after the measurements and can therefore not corrected but should be discarded (see e.g. the occurrence of outliers in the model parameter calibration that cannot be explained by natural processes).

3.5.2 Uncertainties related to uncontrolled environmental boundary conditions

The objective of all long-term measurements is to document trends or sudden changes of the monitored parameter. The uncertainties related to uncontrolled environmental boundary conditions are causing variation in the SPMC that may lead to wrong interpretation of the observations. Even if the protocols are strictly followed and the uncertainties described previously minimized, the measurements from the sensors may not reflect the broader situation as the measuring devices (pile, lander) or the nearby human activities have an influence on the measurements (Bolanos et al., 2011; Fettweis et al., 2016). Further piles, landers or other devices that are in contact with the sea floor may cause local scour and thus morphological, sedimentological and hydrodynamic changes that affect locally the concentration and the inherent properties of the SPM (e.g. Baeye et al., 2016).
4. Towards best practice

To come to best practice for long-term monitoring activities of SPMC an accurate documentation of the successive operations and of the accumulating effect of uncertainties is required. This means thus not only following a standard workflow, but also collecting meta-information about applied protocols, quality standards, error estimations, as well as of additional parameters that characterize e.g. human activities near the measuring site, climatological indicators, river runoff and oceanographic and atmospheric standard parameters.

4.1 Best practice workflow

A brief overview of the generic succession of operations required to run long-term or large-scale measurements of SPM concentrations is depicted in Figure 20. The activities can be divided into phases of pre-measurement, measurement and post-measurement and grouped into planning and resource allocation, accuracy and precision measures and post-processing of observation data and related ancillary information. In long-term observations the three phases and activities are not in strict sequence but interleave. Threats to accuracy and precision that are specific for long-term observations, define the type and timing of measures during the measurement phase to minimize or avoid them. They set the need to allocate steady and flexible operation resources and the set-up of a proper organizational framework linking laboratory and field work. (Near) real-time monitoring of the data is desirable to react promptly with remote or field operations on system failures or other threats to accuracy and precision.

Processing of the data in the post-measurement phase comprises firstly quality safety measures. Finally all data from water samples, sensor output, sensor (inter-)calibration and interpretation parameters that reveal information about the optical and acoustical properties of the suspended particles and their changes are numerically assembled in the models that yield the final SPM concentrations and estimations of uncertainties.

4.1.1 Pre-Measurement Phase

The planning of the layout of the observational device is discussed in the following with respect to achieving the required precision and accuracy of the resulting SPMC. Planning covers the choice of required instrumentation and the resources needed to carry out repeated field operations. The first part deals with the sensitivities and ranges of the measuring devices and with the need of adjoined measurements of state variables such as particle size, shape and composition, salinity, temperature, current velocity or turbulence, see Table 2. The second part covers the maintenance or exchange of instruments, the reaction on sudden system failure; the execution of regular or event-triggered ship surveys for in-situ sensor and model calibration, and the use of elaborate instrumentation to measure other state variables needed for a more
accurate and complete interpretation of the data. Before field usage, all sensors have to be calibrated in the laboratory against standards, to verify providers calibrations and to manifest a reference against any possible changes in sensor response after recovery.

### 4.1.2 Measurement Phase

Once deployed in the field, the observing system remain unattended until the next maintenance service. Processes that disturb the sensor outputs with respect to the preceding sensor and model calibration have been presented in chapter 3. In addition to maintenance with sensor cleansing regular or event-triggered intercalibration by parallel operation of a well-defined reference sensor is recommended to check the functioning of the field systems. The functional understanding of the interrelation between inherent particle properties, system state conditions and sensor SPMC may benefit from additional surveys to estimate the source and magnitude of changes in the sensor SPMC between the in-situ calibration activities.

Ongoing (near) real-time monitoring of sensor output in the land-based lab is very helpful to detect timely system failures, biofouling and other needs for field operations. In this way it feeds back into ongoing planning and allocation of resources.

### 4.1.3 Post-Measurement Phase

Post-measurement starts with the raw data retrieval and their conversion into ascii-based data and archiving information that collate all so far undertaken calibration, accuracy and precision measures (Tzeng et al., 2016). After recovery from the field, optical and (if possible) acoustical sensors should be calibrated again against the lab reference to quantify any changes in sensor response due to electronic drift or optical window damages. In post-processing the data should first undergo an expert judgement to flag e.g. occurrences of spikes, stuck values or unreliable magnitudes. Further, any effects of sensor drift, between sensor differences with regard to lab or field standards, and biofouling effects should be identified and if possible corrected for. The resulting set of accepted and corrected data together with filter weights acts as input for the computation of the sensor SPMC. As the ratios of turbidities to sample SPMCs are in general variable in time, this step is not straightforward but may require some iterative optimization to find of statistically homogeneous sets. Finally, the errors due to all steps in the described work chain have to be figured out. These error estimates are only due to the measurement procedures themselves and yield only the errors at the observing point and for the calibration periods of the time series. Further uncertainties that relate to the representativeness of the measurements in time and space can be substantial for the interpretation of the data in terms of processes and trends.

### 4.2 Discussion and ranking of the uncertainties
All steps along the described chain of activities contribute to the overall error of the final SPMC data set estimated from the combination of sample SPMC and turbidity or acoustical backscatter signals. They comprise random errors that lead (1) to uncertainties of individual SPMC but approximate the accurate value with increasing amount of data; and (2) systematic errors (biases) that lead to an average over- or underestimation of all data. There exist two types of biases: one that is constant or independent of observing times and locations (e.g. from the choice of the regression method, as discussed in § 3.4.2) or changes with the time and location (§ 3.4.3). Some kinds of errors can be detected, and to some extent corrected, whereas, others are inherently associated with the applied technologies and its interference with the environment and remain spurious and difficult to quantify or to control. The first types of errors are related to the sensors, sampling and lab protocols or the modelling techniques used to establish a relation between the sensor output and the sample SPMC, while the latter are mainly related to systematic natural variabilities in SPM inherent properties that may occur during autonomous measurements. In table 3 we have listed the sources of uncertainties as described in chapter 3, and added the percentage error (1 standard deviation), being detectable and correctable and random or systematic (bias). For the levels of uncertainty we further distinguish cases with and without applied corrections. The listed numbers refer to our examples in chapter 3, and only some of them can be regarded as general. Rather they represent typical values that indicate their relative importance for the overall error. The following discussion continues along the vertical order of table 3, which reflects the structure of chapter 3 and relates more or less directly to the major items of the workflow depicted in Figure 20.

4.2.1 Sensor related uncertainties
Most sensor related sources of uncertainty in the workflow can be deduced from the correct ratio of the sensor signal to a standard solution (e.g. formazine). Any deviation from the 1:1 ratio results in a bias that will pass through the whole workflow and needs to be detected and corrected for. As long-term and large-scale observation often employs more than one sensor the homogeneity of the data sets may be not preserved. This is also the case when just one sensor is used but its signal response changes with time. The example for the 11 Seapoint© turbidity sensors described in §3.1.1 should be taken as a token to validate the factory calibration before its first field deployment, also to have trustable baseline to detect any sensor response drift over time. The shown examples of sensor drift were due to delivered power decrease (in case of battery depletion this can be up to 100%) or to the degradation of optical window surfaces that may become scratched or opaque by repeated impact of sharp-edged particles. Controlling such a sensor drift will require either the close follow up of the battery
voltage and indirect field inter-calibration against a well calibrated reference sensor operated in parallel very close to the long-term observing location, or by regular re-calibration checks in the laboratory with formazine or other reference solutions after recovery of the sensor. This allows the intermittent adaptation of voltage to standard solution units and at least some correction for the sensor drift for the times between inter- or re-calibration.

Another type of uncertainty is the usage of sensors that are not adapted to the range of turbidity values of the site. As found in the example in §3.1.2, this may reduce the overall accuracy of the output in general by a bias of about 2% up to 24%. This error can in principle only be corrected for by intense calibration sampling but the limited resolution in turbidity may also increase the random variability in the ratio of sample SPMC to turbidity. Accuracy of the measurements can easily be increased by matching the in-situ turbidity with the designed range of the sensors and/or by using two or more sensors to cover a larger turbidity range.

Inter-sensor variability may result from uncertainties related to the so-far discussed items. The comparison of the SPMC derived from different OBS3+ sensors (§ 3.1.3) shows that inter-sensor variability for identical sensor types can be reduced to natural random fluctuations in the water bodies, if all sensors are calibrated separately against sample SPMC. If inter-comparing different types of sensors, it is not evident beforehand that even separate calibration leads to the same results for longer time series, as different sensors may react differently to changes in the IOPs of the SPM. This may result in time-dependent biases and has to be investigated case by case.

4.2.2 Environmental related uncertainties

Biofouling represents the largest challenge for accurate measurements of turbidity and in some cases of acoustical backscatter intensity in the field. If not detected and flagged, the bias (positive for turbidity; negative for acoustical backscatter) can easily reach many tens of percent. Especially optical sensor output is sensitive to increasing coverage of the sensors material disturbing the light pathways or scatter detection volume. Although technologies, such as wipers or irradiation with UV light (Bueley et al., 2014) exist to mitigate the impact of fouling, their applicability might be limited in many coastal waters during seasons with high biological productivity, so that regular cleansing of the sensors remains a necessity and needs to be properly considered when allocating ship and personal resources. Sensor cleansing needs to be accompanied by sensor inter-calibration against a reference device. Correction of the bio-fouled data has been shown for an acoustic profiler sensor (ADCP, ADP) in §3.2.1 and is described in literature for biofouled OBS data (e.g. Dolphin et al., 2000), however, the methods are case specific. As long as the effect of biofouling is limited corrections by means of independent not-affected devices is sometimes possible. In many cases, however, tagging and discarding bio- fouled data is the only option.
Air bubbles enhance the turbidity and acoustical backscatter signals. As long as their presence can be detected they can be tagged and discarded.

Very high SPMC may produce backscatter intensities that saturate the sensor output. It is straightforward to tag these data. Discarding them will introduce a bias for the periods of very SPMC. Modelling the gaps by e.g. extending the power spectrum of the time series will lead to more realistic values. The degree of uncertainty cannot be provided numerically here as it is dependent on the specific situation and applied interpolation model. To mitigate this effect one simply has to use a type of sensor with higher output range. This case nicely demonstrates the need of adequate planning in the pre-measurement phase, the need of ongoing monitoring and the capabilities in allocating resources to exchange sensors in due time.

### 4.2.3 Sample related uncertainties

The determination of sample SPMC is through three steps, sampling, filtering and subsequent weighing. The sampling involves systematic uncertainties that are related to the sampling technique, the sampling volume in relation to the temporal variability of the SPMC, and to the exact location of the sample versus the sensor. Weighting is considered a minor source of error. The main uncertainties involved are related to the filtering procedure at SPMC <3 mg/l, because the weights of the filter loadings are in the order of the sample specific filter offset. So far the only and most accurate protocol is the method with different filter volumes, where sample SPMC is determined by the linear regression of filter loading weight versus filtered volume, which cancels out the filter offset. At SPMC >25 mg/l the error without knowing the filter offset amounts to 3%, but raises to 50 % for SPMC <3 mg/l. Using the different volume method reduces the uncertainties to less than 10 % for SPMC <3 mg/l. For SPMC >25 mg/l the impact of the filter offset becomes negligible. Using only one filter in this range bears the risk that faulty sample SPMC cannot be identified and show up as outliers in the scatter plots that cannot be removed from the calibration data set. This can be avoided by working with e.g. triplicates and removing the sample that differs from the other two by more than a pre-defined value which reduces the random error by a factor of 2 down to the order of 5% and less.

As a simple method to evaluate the quality of the sample SPMC compared with in situ optical measurements we refer to the obviously generally valid close relationship between sample SPMC and Hach turbidity (Figure 21). Large inconsistency between the Hach sample turbidity measured on board with a well-defined subsample, in-situ turbidity and sample SPMC would designate this sample as unreliable.

### 4.2.4 Choice of the linear regression model

This source of uncertainty has some significance as it is systematic and leads to SPMC that are all either to high or to low. It is quite evident that a calibration data set within an $R^2 > 0.9$ should
be achieved to keep uncertainties involved with the choice of a specific regression model well below 10%, independent of the model and the range of the calibration data compared to the complete data set. Please note that this statement refers only to the choice of the regression model and not to any systematic changes in the IOPs or IAPs beyond the sample calibration period. Any random uncertainties created in the former steps of the workflow have therefore be kept as small as possible. Even then, in waters with highly variable conditions over the sample calibration period, such a high $R^2$ may not be achievable. In this case we recommend to use either the Eigenvalue regression or averaging between regressions with exchanged dependent and independent variables. Visual inspection indicated that this mean regression follows nicely the linear trend of the data independent of $R^2$.

Regressions to log$_{10}$-transformed data exhibit a generally higher sensitivity to the model choice for $T_{urbNorm} > 0$ that increase substantially for turbidities above the calibration data. In this respect, regressions with log10-transformed data bear the risk of substantial biases in the SPMC computed from higher optical turbidity or acoustical backscatter data. For low turbidities, the sensitivity is low as after re-transformation, regression are forced to meet the data origin point. For acoustical data, $R^2 > 0.9$ is difficult to achieve and model choice sensitivity is even further enhanced as the dB-signal has to be raised to the power of 10. Hence the use of acoustical devices for SPMC-estimation seems to be accompanied with large uncertainties at this step of the workflow.

### 4.2.5 Variabilities in SPM inherent optical and acoustical properties

Uncertainties due to undetected changes in inherent optical and acoustical particle properties of the SPM are difficult to quantify or control during long-term SPMC measurements. Most of them can be ascribed to changes in particle size, shape, composition and density. Regular water sampling to compare filter weights (the sample SPMC) with sensor output in parallel post-processing will provide insight into the stability/variability of models used to estimate sensor SPMC over time and/or space. The examples of §3.4.3 show that even intra-tidal variations or events of several hours duration lead to systematic uncertainties of 50% to 200% demonstrating the significance of this effect for specific sites and periods. Therefore it is recommended to add further sensor technologies to the observing system that give direct indication for changes in the IOPs and IAPs, e.g. when particle size or composition is expected to change beyond previous uncertainties and systematically at the observation site (Table 2).

### 4.3 Turbidity as a surrogate for SPMC?

#### 4.3.1 Uncertainty between SPMC and turbidity

To separate variability due to measurement errors from variability due to natural variations in IOPs protocols that use the same water sample for filtration and for turbidity estimation should
be used in parallel to the in-situ procedures. Figure 21 shows a collection of sample SPMC
versus turbidity measurements of the same water sample recorded with a portable ISO Hach
2100P nephelometer from various waters around the world (North Sea, English Channel,
Mediterranean Sea, Rio de la Plata, French Guiana nearshore, Gironde estuary, Scheldt estuary,
see Table 3), collected by the RBINS (Dogliotti et al., 2015; Knaeps et al., 2015) and HZG
(Röttgers et al., 2014). The protocols for sample SPMC and turbidity measurements are those
described in Neukermans et al. (2012a) for RBINS and Röttgers et al. (2014) for HZG. The figure
shows that the ratio between sample SPMC and Hach turbidity is quite stable within an
uncertainty of 20% throughout the regions. In this collection, 4.1% of couples fail outside of the
95% confidence interval regarding the t-distribution of sample SPMC/turbidity in the
logarithmic space. The outlying couples probably reflect the tails of the combined natural
variability of particles mass-specific side-scattering coefficient, and sampling and filtration
errors. The average ratio of sample SPMC to turbidity from all data is about 1.13 mg/l/FNU
(RBINS data), and 1.19 mg/l/FNU (HZG data).

Despite calibration to a formazine reference solution and the use of ISO-normed optical
sensors, model calibration may vary considerably in recorded turbidity for a same SPMC
solution across different instruments resulting in instrument-specific turbidity-SPMC relations,
see Figure 22. Although different types of optical sensors have been calibrated against a
reference solution, they yield up to 20% differences results in the field. Another example
corns data collected by Ifremer and the University of Rouen at different locations in the
Seine estuary (Druine et al., 2018) with a ISO Hach 2100N nephelometer (same constructor, but
different type as the above mentioned 2100P) give significant different turbidity values for the
same SPMC. We assume, given the stability of the Hach 2100P over a wide range of areas that
the deviations are mainly caused by the instrument specificity. The latter was confirmed during
intercalibration of both ISO standardized nephelometers with StablCal Formazin and with SPMC
solutions.

4.3.2 Need for further sample SPMC?

Nevertheless similar outputs against a reference solution, optical sensors have different
sensitivities to the inherent properties of the SPM. This prohibits comparing the turbidity values
measured by different type of optical sensors. Despite differences in turbidity readings for a
given SPMC, well correlated relationships between instrument specific turbidity and sample
SPMC can be established during model calibration. The generally high correlation between
sensor specific turbidity and sample SPMC show that turbidity as a surrogate of SPMC is
reliable, as long as site-specific (model) and instrument-specific (sensor) calibrations are carried
out. Although differences have been observed in turbidity recordings between different sensors
the data in Figure 21 show that the relationship between SPMC and turbidity is quite stable throughout different localities for a same sensor type when a similar protocol is followed. This relationship could be used as a first estimate of SPMC from a turbidity values without collecting sample SPMC for model calibration and underlines the importance of a well calibrated reference system. The Figure 22 also shows that nephelometers that follow the ISO protocol are not giving the same value; this means that even following the same protocols at the same site and periods turbidity is a vague unit to estimate SPMC. It strengthen further that any turbidity unit should be referred to the instrument used and the protocol applied, hence the many turbidity units (see § 2.1).

Considering the stable ratio of Hach-turbidities to sample SPMC over a broad range of coastal regions it may be interesting to address the question whether one could use the scaled Hach turbidities instead of sample filter weights. The former ones introduce a random uncertainty of some 20%, but the advantage are less laboratory effort and therefore more available calibration data. The site specific regressions for sample SPMC versus Hach turbidities vary by only 20% for the RBINS data set shown in Figure 21. Using the global fit at different sites still reproduces the sample SPMC within less than 20% with an average bias of 3%. Especially given the high uncertainties of low sample SPMC due to the filter offsets that can only be controlled by several filters per sample, a 20% random error for Hach-derived SPMC seems to be a suitable and cheap alternative to filter weights.

The sample SPMC and the sensor data should preferably be collected in-situ as it is more reliable than in lab model calibrations (ISO, 2014). In case no in situ samples can be collected or if the range of sample SPMC is too small, in lab model calibration can be applied with representative samples. Bollen et al. (2006) describes a laboratory model calibration using a representative in-situ bed sample taken near the monitoring station. The bed sample was sieved on a 63µm sieve, followed by desalination and drying, to finally produce standard solutions with defined SPMC that have other IOP then the sample SPMC. The regression model using in-situ data only has a larger slope compared to the relation derived from the standard SPMC solution and will overestimate the sensor output by about 10%.
5. Conclusions and Outlook

Optical and acoustical sensors have proved invaluable in the study of SPM dynamics in marine and estuarine environments as they allow collecting easily in-situ, high-frequency SPMC time series over long periods of time. The payback is the availability of large homogenous data set of SPMC from various locations on the globe; the drawback is that the quality or certainty of the data and thus also the inter-comparability depends on factors that are only to a certain level avoidable. The factors that hamper the quality of the data have been described in chapter 3 and grouped according to the functioning of the sensor, the environment, the collection of sample SPMC for calibration, the calibration using linear regression models, the inherent optical and acoustical properties of the SPM and human errors (see Table 3). While the first four types of errors are detectable and sometimes correctable, the relation of sensor output to environmental condition is difficult to detect outside the calibration period. The latter affects the inherent properties of the particle and can result in over- or underestimation of the SPMC by up to factor 2 or more. A good understanding of the processes that are causing changes in SPM concentration and particle inherent properties (size, shape, density and composition) is required in order to estimate their importance and to possibly rescale the sensor data to some reference particle properties. Further the use of both acoustic and optical sensors extended by additional sensors that measure size and composition of the SPM (see Table 2) is a measure to identify changes in inherent particle properties. For long-term observations with remote stand-alone systems this presently requires unsurmountable effort. As a consequence, intensive measuring campaigns remain necessary to understand the variability in the relation between sensor output and sample SPMC that can allow a correction of the sensor data.

Acoustical and optical sensors require both the conversion of the sensor output (after sensor calibration) to a mass concentration. This is done by relating the sensor output to a reference SPMC, which is preferably the sample SPMC. The choice of the regression method, the dependent and independent variable and the error associated with the reference SPMC determines the coefficient of determination and the values of the regression. We have build a model that based on the R² and the normalized turbidity/dB quantifies the uncertainty of the sensor derived SPMC in the calibration range and outside of it.

Our study confirms that the relation between turbidity and sample SPMC is depending on protocols (EPA, ISO), technology (scattering angle) and the manufacturer, and even may differ between sensors of the same type (e.g. Downing, 2006; Rai and Kumar, 2015; Rymszewicz et al., 2017). The relation between the output of an acoustical sensor and SPMC is even more variable. In spite of these uncertainties, turbidity is still often used as a proxy for water clarity or SPMC as is the dB of acoustical sensors. We advice to not use turbidity (or dB) for scientific
purposes as it diminishes the comparability of the data. Instead, the sensor output needs to be
transformed into a mass concentration, a unit that is comparable in time and between regions.
If this is not possible, then the turbidity data should always be referred to the instrument used
and the protocol applied. The problem aggravates when turbidity data that have been collected
using different technologies and protocols over long periods of time and regional scales are
stored in international databases (e.g., turbidity in EMODnet, see http://www.emodnet.eu),
and used to derive conclusive trends of the environmental status of marine and estuarine
areas. The uncertainty analysis presented here could be the basis for further validation of
existing historical data of turbidity and SPMC by estimating the uncertainties related to the
measurements and could offer guidelines to obtain intercomparable high quality long-term
SPMC time series in the future.
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Table 1: Bulk mineralogical composition (in %) of the SPM in the English Channel and southern North Sea sampled with a centrifuge during transect or anchoring of the vessel. Offshore Somme mouth, Dover Strait, Calais, Zeebrugge and north of the Rhine mouth. Qtz=Quartz; Kspar=K-feldspar; Plag=Plagioclase; Carb=Sum of Calcite, Mg-rich Calcite, Dolomite, Aragonite; Am=Amorphous fraction (organic matter and biogenic opal); Hal=Halite; NClays=Sum of non-clay minerals; Kaol=Kaolinite; Chl=Chlorite; 2:1=Sum of 2:1 clays and micas; Clays=Sum of Kaol+chl+2:1. The samples have been collected with a centrifuge (water intake about 4 m below surface) and analysed with XRD (data from Adriaens et al., 2018).

<table>
<thead>
<tr>
<th></th>
<th>Qtz</th>
<th>Kspar</th>
<th>Plag</th>
<th>Carb</th>
<th>Am</th>
<th>Hal</th>
<th>NClays</th>
<th>Kaol</th>
<th>Chl</th>
<th>2:1</th>
<th>Clays</th>
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<tbody>
<tr>
<td>Somme</td>
<td>29</td>
<td>2</td>
<td>3</td>
<td>30</td>
<td>15</td>
<td>5</td>
<td>86</td>
<td>&lt;1</td>
<td>&lt;1</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Dover Strait</td>
<td>22</td>
<td>3</td>
<td>2</td>
<td>21</td>
<td>18</td>
<td>7</td>
<td>84</td>
<td>2</td>
<td>4</td>
<td>20</td>
<td>26</td>
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<tr>
<td>Calais</td>
<td>10</td>
<td>1</td>
<td>&lt;1</td>
<td>29</td>
<td>22</td>
<td>3</td>
<td>66</td>
<td>&lt;1</td>
<td>2</td>
<td>31</td>
<td>33</td>
</tr>
<tr>
<td>Zeebrugge</td>
<td>20</td>
<td>1</td>
<td>5</td>
<td>24</td>
<td>10</td>
<td>2</td>
<td>61</td>
<td>2</td>
<td>4</td>
<td>33</td>
<td>39</td>
</tr>
<tr>
<td>Rhine offshore</td>
<td>29</td>
<td>4</td>
<td>1</td>
<td>21</td>
<td>12</td>
<td>3</td>
<td>70</td>
<td>1</td>
<td>2</td>
<td>27</td>
<td>30</td>
</tr>
<tr>
<td>Rhine nearshore</td>
<td>17</td>
<td>4</td>
<td>2</td>
<td>21</td>
<td>16</td>
<td>1</td>
<td>61</td>
<td>2</td>
<td>1</td>
<td>35</td>
<td>38</td>
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Table 2: List of additional state parameter and their measuring methods that are necessary to interpret the results of long-term SPMC measurements with more accuracy and completeness (sensor: instrument that can be used in long-term measurements; water/centrifuge sample: can be measured occasionally; station: nearby meteo, tidal, or wave station; LOI=loss of ignition, POC=particulate organic carbon, PON: particulate organic nitrate, XRD: x-ray diffractometer).

<table>
<thead>
<tr>
<th>State parameter</th>
<th>Method</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Particle size in situ</td>
<td>laser diffractometer, holography, optical camera systems</td>
<td>sensor</td>
</tr>
<tr>
<td>Particle size in lab</td>
<td>Grain size analysis (primary particle size)</td>
<td>water sample, centrifuge sample</td>
</tr>
<tr>
<td>Particle composition</td>
<td>LOI: Organic matter</td>
<td>water sample, centrifuge sample</td>
</tr>
<tr>
<td></td>
<td>Element analysis: POC, PON</td>
<td></td>
</tr>
<tr>
<td></td>
<td>XRD: Mineral composition</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Pigment analysis: Chlorophyll</td>
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</tr>
<tr>
<td></td>
<td>Colorimetric analysis: TEP concentration</td>
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<tr>
<td></td>
<td>Electron microscopy</td>
<td></td>
</tr>
<tr>
<td>Particle composition</td>
<td>Fluorimeter: Fluorescence</td>
<td>sensor</td>
</tr>
<tr>
<td></td>
<td>Primary production: Fast Repetition Rate</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fluorimeter</td>
<td></td>
</tr>
<tr>
<td>Particle shape</td>
<td>Holography, floc camera</td>
<td>sensor</td>
</tr>
<tr>
<td></td>
<td>Electron microscopy</td>
<td>water sample</td>
</tr>
<tr>
<td>Turbulence</td>
<td>High frequency Acoustic Doppler Sensor</td>
<td>sensor</td>
</tr>
<tr>
<td>Currents</td>
<td>Acoustical Doppler Sensor</td>
<td>sensor</td>
</tr>
<tr>
<td>Waves</td>
<td>Acoustic Doppler Profiler, Wave rider, floater</td>
<td>sensor or station</td>
</tr>
<tr>
<td>Density</td>
<td>Conductivity, Temperature</td>
<td>sensor</td>
</tr>
<tr>
<td>Water level</td>
<td>Pressure sensor; tide gauge</td>
<td>sensor, station</td>
</tr>
<tr>
<td>Distance to bed</td>
<td>Acoustic altimeter</td>
<td>sensor</td>
</tr>
<tr>
<td>Meteo</td>
<td>from relevant meteo stations</td>
<td>station</td>
</tr>
</tbody>
</table>
Table 3: Quantification and nature (random or bias) of uncertainties (in % based on normalized RMSE) from the examples described in chapter 3. Negative (positive) bias corresponds to an underestimation (overestimation) of the actual value.

<table>
<thead>
<tr>
<th>Source of uncertainty</th>
<th>Detectable</th>
<th>Correctable</th>
<th>Uncertainty without correction</th>
<th>Uncertainty with correction</th>
<th>Comment</th>
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<tr>
<td></td>
<td></td>
<td></td>
<td>without correction</td>
<td>with correction</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>random bias</td>
<td>random bias</td>
<td></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>3.1 Sensor</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.1.1 Factory calibration</td>
<td>yes</td>
<td>yes</td>
<td>-</td>
<td>± 15%</td>
<td>less than ± 2%</td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.1.1 Optical degradation</td>
<td>yes</td>
<td>yes</td>
<td>-</td>
<td>-20%</td>
<td>±5%</td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>3.1.1 Voltage supply</td>
<td>yes</td>
<td>yes</td>
<td>-</td>
<td>-90%</td>
<td>±10%</td>
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<tr>
<td></td>
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<tr>
<td>3.1.2. Sensitivity of sensor</td>
<td>yes</td>
<td>no</td>
<td>&lt;25%</td>
<td>no example</td>
<td>no example</td>
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<td></td>
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<tr>
<td>3.1.3 Inter-sensor variability</td>
<td>yes</td>
<td>no</td>
<td>2%</td>
<td>no example provided</td>
<td>no example provided</td>
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<tr>
<td><strong>3.2 Environment</strong></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>3.2.1 Biofouling</td>
<td>yes</td>
<td>no¹, yes²</td>
<td>-</td>
<td>positive, large (up to &gt;100%)¹</td>
<td>f(no of beams)², data loss¹, partial data loss²</td>
</tr>
<tr>
<td></td>
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<tr>
<td>3.2.2 Saturation</td>
<td>yes</td>
<td>no</td>
<td>Negative¹</td>
<td>-</td>
<td>-</td>
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<td></td>
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<td></td>
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<tr>
<td>3.2.2 Ambiguity</td>
<td>yes</td>
<td>yes</td>
<td>not specified</td>
<td>-</td>
<td>-</td>
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<td></td>
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<tr>
<td>3.2.3 Air bubbles</td>
<td>yes</td>
<td>no</td>
<td>-</td>
<td>no example provided</td>
<td>no example provided</td>
</tr>
<tr>
<td></td>
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<tr>
<td><strong>3.3 Sample</strong></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>one filter triplicate filter volume</td>
<td>yes¹</td>
<td>no</td>
<td>2%-10%</td>
<td>1%-6%</td>
<td>1%-50%³</td>
</tr>
<tr>
<td>method</td>
<td>yes¹</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>yes²</td>
<td></td>
<td>3%</td>
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<tr>
<td><strong>3.4 Model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.4.2 Regression model</td>
<td>yes</td>
<td>no</td>
<td>10%-60%¹</td>
<td>0-&gt;30%¹,²</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.4.3 Inherent particle properties</td>
<td>yes¹</td>
<td>partly</td>
<td>±50%²</td>
<td>40%-60%³, 50%-200%⁴</td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.4.4 Optic vs. acoustic sensors</td>
<td>yes</td>
<td>no</td>
<td>50-100%²</td>
<td>40%¹, O(100)%²</td>
<td></td>
</tr>
</tbody>
</table>

¹optical sensors
²acoustical sensors with >3 beams
³numerically not specified
⁴data loss
⁵optical and acoustical sensors
⁶only random uncertainty
⁷random + bias
⁸random bias per sample ; depends on SPMC (>50-<1 mg/l)
⁹_only with sample SPMC
¹⁰geographical variation, Figure 14
¹¹organic content, Figure 15
¹²sand in suspension, Figure 16+17
¹³acoustic sensor calibrated with sample SPMC, Figure 18
¹⁴acoustic sensor calibrated with OBS, Figure 18, 19
Figure 1: Organic matter (OM) content in the SPM from the Seine estuary and the Gulf of Lions (left) determined through Loss-on-Ignition (LOI) and Particulate Organic Carbon content from the Southern Bight of the North Sea (right) determined through element analysis. The OM data are about four times larger than the POC data (Grove and Bilotta, 2014). Both data set show that largest variation in organic matter content occurs at low SPMC.
Figure 2: Factory and in lab sensor calibration of two OBS3+ (8729 and 8849). The laboratory calibration was done after 421 (8729) and 329 (8849) days of measurements in high turbid (SPMC > 1g/l) sea water during the period 2014-2016. The solid lines are the 2nd order polynomial fittings provided by the factory, the dashed lines are the 2nd order fittings after recalibration.
Figure 3: (a) Power provided by an external source to an OBS3+ (T8549) measuring in high and low range in a standard solution of 2000 AmcoClear® equivalent BU. When the voltage drops below 6 V, the sensor registers low voltage output values. (b) SPMC time series from the Belgian nearshore measured with an OBS3+ that was attached to a SonTek Hydra data logging system for storage and battery supply. The system was replaced on day 118.7 by a similar system. The first system was not providing the minimum of 6V to the OBS, the second system worked correctly. In blue is shown the corrected time series.
Figure 4: Inter-sensor variability between three OBS3+ sensors measuring at about 50 cm from each other during a tidal cycle (Belgian nearshore area). The sensors have been calibrated using the same sample SPMC. The differences between the OBS’s are not constant but change during the course of the tide. This points possibly to variations in the SPMC (sensor are located about 50 cm from each other) or to different sensitivities of the individual sensors.
Figure 5: The time series collected in the Belgian nearshore area show the OBS derived SPMC at 0.2 and 2 mab (left axis) and the ratio between SPMC at 0.2 and at 2mab (right axis). The thick lines are the low-passed filtered data. The OBS at 0.2 mab was covered by barnacles, while the one at 2 mab was not affected by biofouling. The low-pass filtered ratio indicates that biofouling started to affect the OBS at 0.2 mab from about day 134 onward. The OBS at 0.2 mab saturated during the measuring period when the SPMC exceeded about 1.6 g/l.
Figure 6: 35-day time series of maximum backscatter ratio (up) and the backscatter strength (down) recorded by an upward-looking 1.2 MHz RDI ADCP (5th bin at about 1.5 m above the ADCP is shown) moored offshore the Belgian coast. Changes in the maximum backscatter ratio, $R_v$, occurred from day 165 onward and from day 172 a gradual increase is observed. Superposed are quarter-diurnal variations in $R_v$ of the order of 2-3 dB that result from the deposition of fine sediments during slack water and the subsequent erosion during increasing currents. The recovered ADCP was massively fouled by barnacles, tube building worms and hydrozoa.
Figure 7: 9-day time series of the backscattering strength vertical profile recorded by an upward-looking 500 kHz ADCP (Nortek ADP) moored on the sea bottom at 20 m depth in the Bay of Vilaine, South of Brittany (France). The surface oscillation corresponds to the tidal elevation. a) Volume backscatter strength measured by the transducer 1. At day 152 a biofouling event caused a sudden drop in all backscatter values of the profile, by nearly 10 dB. Following, backscatter values rise again and drop again until day 153. b) Maximum backscatter ratio $R_v$. Biofouling events on other transducers are identified at days 149 and 151. c) Median backscatter strength. The median allows a computation of a backscattering strength without perturbations by the biofouling.
Figure 8: Typical bell-shaped backscatters curve of an OBS (Sottolichio et al., 2011), meaning that a given OBS output can correspond to two SPMC values. The figure shows how this ambiguity can be solved by using two superimposed sensors. Left: when the upper probe records lower turbidity than the lower probe, upper concentration is solved, but the lower remains unsolved. Right: when the upper probe records higher turbidity than the lower one, lower concentration is solved, but the higher remains ambiguous and unsolved.
Figure 9: Relating sample SPMC to sensor output using different linear regression models for the actual and the log transformed data. The data have been collected in the Belgian nearshore area and consist of 26 sample SPMC and corresponding turbidity values from a Seapoint OBS. The solid lines correspond to the relationship $BU = f(\text{sample SPMC})$ and the dash lines to sample $\text{SPMC} = f(BU)$. 
Figure 10: Direct calibration of a profiling acoustic sensor (Nortek AWAC) against sample SPMC in a moderately turbid environment (<100 mg/l) located at the mouth of the Seine estuary (red dots: surface samples, blue dots: bottom samples).
Figure 11: Relating OBS derived SPMC to the backscatter intensity of the first bin of two Sontek 3 MHz ADP profilers (M284, M947) using linear regression models. The data set consists of about 1 year data collected in 2013 in the Belgian nearshore area; every sensor measured about half of the period. The bold lines are the mean of 8 different regression models (Least square, Eigenvalue, Theil-Senn, Robust fit and each one with interchanging dependent and independent variables), the dashed lines are the regressions lines (M284: $R^2=0.4$; M947: $R^2=0.6$).
Figure 12: Mean spread of the slopes of the regression lines (maximum – minimum) with respect to the normalized turbidity ($\text{Turb}_{\text{norm}}$) as a function of the mean $R^2$ over all regressions (mean regression over the 7 regression models in the linear domain). The slope of the curve for $\text{Turb}_{\text{norm}}=0$ is close to zero. For higher and lower $\text{Turb}_{\text{norm}}$ values the spreading and thus the uncertainty increases. The uncertainty of the model increases with decreasing $R^2$. 
Figure 13: Mean spreading of the regression (maximum – minimum) for the different regression models as a function of the normalized turbidity for left the linear scale and right the log<sub>10</sub> transformed data. The examples show the spreading for data sets with $R^2<0.75$ and for $R^2>0.90$. The black lines are the 10 and 90% percentiles of the data.
Figure 14: Sample SPMC as a function of Seapoint turbidity collected at various locations in the southern North Sea. The regression is calculated with the Eigenvalue model. The mean regressions are (SPMC=ax+b): all data ($R^2=0.88$; $a=1.53$, $b=-1$); Jade ($R^2=0.83$; $a=1.96$, $b=-16$), Weser ($R^2=0.83$; $a=1.66$, $b=-20$); Hoernum Bight ($R^2=0.95$; $a=1.44$, $b=0$); German Bight ($R^2=0.99$, $a=1.05$, $b=1$); Oosterschelde ($R^2=0.74$; $a=2.34$, $b=-3$); Belgian coast ($R^2=0.60$, $a=1.91$, $b=-1$).
Figure 15: Sample SPMC and turbidity collected in the tidal inlet between two islands in the German Wadden Sea between 10 and 19 May 2011 (Becherer et al., 2016). Sample SPMC ranged between 7 mg/l and 500 mg/l, during the storm (14-17/05) no samples have been taken. (a) Time series of the ratio turbidity/sample SPMC and (b) dependence of the specific backscatter $b = \text{turbidity} / \text{sample SPMC}$ on total organic carbon. All samples shown are taken after the storm, from 17th through 19th May. Surface data are taken 1 m below water surface.
Figure 16: Relation between optical (YSI, type 6920 V2) and acoustical backscatter sensor (ADV (Nortek, 6MHz) at a muddy (location 1) and a sandy bed site (location 2) located 1200m apart in the main tidal channel of a brackish marsh located in the Scheldt estuary during 2 tidal cycles (Schwarz et al., 2017).
Figure 17: Changes in the ratio of turbidity to sample SPMC from 0.4 to 0.12 during a storm period in the Elbe estuary caused by the resuspension of sand grains.
Figure 18: The model SPMC uncertainty (normalized RMSE and residuals) as a function of the reference SPMC (sample or sensor derived SPMC) and SPMC (see the dataset shown in Figure 10 and 11) for an acoustical and optical backscatter sensors. The reference SPMC is from sample or OBS3+ derived SPMC.
Figure 19: The model SPMC uncertainty for the ADP’s of Figure 11 expressed as normalized RMSE and normalized residual for different regression models and as a function SPMC. Negative residuals have a higher ADP-derived SPMC than the OBS-derived one.
Figure 20: Workflow of activities and tasks to be performed in long-term SPMC measurements. The arrows indicate the flow information between the tasks and activities over the measurement phases. The measurement phases are plotted in serial order, but may overlap in the course of long-term installations.
Figure 21: Scatterplot of sample SPMC (mg/l) versus turbidity measurements from various waters around the world. The turbidity data from RBINS and HZG have been collected with a Hach 2100S and those from Ifremer and University of Rouen by a Hach 2100N IS. HZG measurements were collected from 2009 to 2013, RBINS data are from 2007 to 2015 and Ifremer and University of Rouen data from 2015-2016. The black line is the 1:1 and the grey lines are the 1:70% and 1:130% lines respectively.
Figure 22: The performance of different sensors (side-scattering: Hach; backscattering: OBS3+ and Wetlabs) during sensor calibration with different Formazin solutions (left) and as compared with natural SPM samples.