

Assimilating Remotely Sensed Suspended Particulate Matter in a 3D Transport Model of the Dutch Coastal Zone

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Abstract

Suspended Particulate Matter (SPM) is an important environmental parameter in coastal seas such as the North Sea as it influences underwater light conditions. Our description and understanding of the complex dynamical SPM transport system can be much improved by means of an integration of remote sensing data and numerical modeling. In this paper, the data assimilation technique, Ensemble Kalman Filter (EnKF), is used to assimilate the remote sensing data of Suspended particulate matter (SPM) from the MEdium Resolution Imaging Spectrometer instrument (MERIS) sensor on ESA's ENVISAT in the computational water quality and sediment transport model, Delft3D-WAQ. The objectives are to determine SPM concentrations and calculate the flux of marine silt along the Dutch coast. SPM data products retrieved from MERIS RR ocean color, when they include information on the uncertainty in the data, are very suitable to be used to update the Delft3D-WAQ sediment transport model in an Ensemble Kalman Filtering approach. For this aim, an optimal set of parameters consisting of SPM concentrations, error products and an approximation of optical depth was derived from MERIS data using the HYDROPT algorithm. This algorithm comprises a forward model based on inherent optical properties (IOPs) and radiative transfer modeling with Hydrolight, and an inverse model to estimate SPM from MERIS reflectance. These parameters were checked for: (1) accuracy of near-shore bio-optical retrieval and atmospheric correction algorithms, (2) possibility to capture change between observations under conditions of non-uniform spatio-temporal coverage, (3) optical depth versus depth of model layers and depth of stratification. The robustness of both data and model are prerequisites for a successful Kalman Filtering. Eventually, the assimilation of the mostly daily MERIS observations enables to overcome the limitations of cloud cover and restriction to the sea surface layer inherent to space borne ocean color observations.

1. Introduction

Fine-grained suspended particulate matter (SPM) is composed of small particles of both organic and inorganic origin. SPM plays an important role in the ecology of shelf seas, for instance in the southern North Sea and adjacent Wadden Sea and estuaries. SPM influences the underwater light climate, which is an important environmental condition for plankton growth. The organic content of fine sediments is also an important food source at the basis of the food web. Finally, the transport and fate of SPM influences the fate of attached micro-pollutants and trace metals.

Figure 1 shows an instantaneous view of the color of the surface waters of the southern North Sea. This coastal transport system is characterized by highly variable concentrations in time and space: resuspension events during high wave conditions, formation of eddies and meanders, variable river inflow all contribute to the complexity. An illustration of the high temporal variability is obtained from high-resolution *in situ* measurements by means of Optical Backscattering Sensors (OBS) mounted on a *Smartbuoy* deployed by Cefas (Lowestof, UK) and the Dutch Rijkswaterstaat (RWS) in 2001 (see Figure 2).

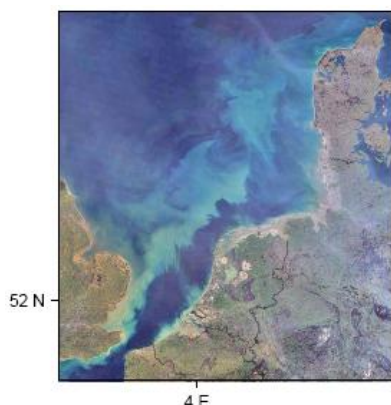


Figure 1 MODIS (Terra) recording of the southern North Sea, March 26, 2007, illustrating spatial distribution of suspended matter in the surface water. (Image courtesy MODIS Rapid Response Project NASA/GSFC)

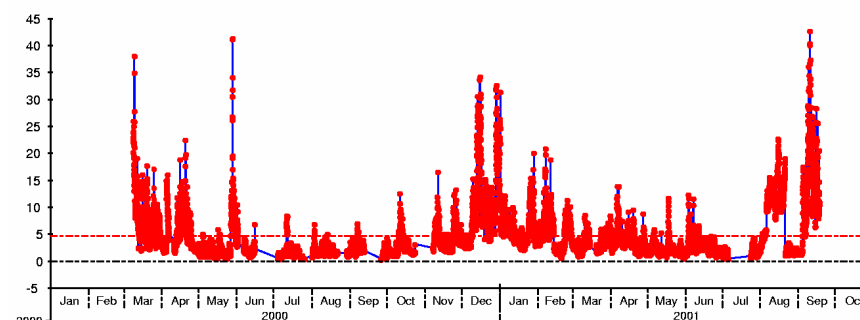


Figure 2. Time series of SPM surface concentration observed by the OBS on the Cefas-Rijkswaterstaat Smartbuoy mooring 10 kilometers off Noordwijk. Dashed red line denotes temporal mean.

Analysis of these data has shown that, in the Dutch coastal zone, autocorrelation time scales are of the order of 7 days. Spatial correlation scales are estimated to be several tens of kilometers along-coast.

Both *in situ* and remote sensing techniques will have their limitations when sampling such a heterogeneous system. *In situ* samples are mostly sparse in space and time, optical remote sensing will only measure a certain surface layer whereas a large portion of the SPM is found near the bed. To overcome the practical limitations to either source of information, we assimilate remotely sensed SPM concentrations in a numerical transport model by means of Ensemble Kalman Filtering (EnKF) (Evensen, 2003).

Traditionally, monitoring has been based on regular ship cruises, occasionally extended with dedicated field campaigns. Consequently, our observation-based description of the coastal SPM transport system has often been limited to spatial and temporal scales of tens of kilometers and weeks, respectively, missing smaller scale spatial features or temporal events. However, with the arrival of reliable ocean color remote sensing data (e.g., from SeaWiFs, and more recently, NASA's MODIS sensors and ESA's MERIS sensor) higher frequency, synoptic mapping of seas surface SPM has become feasible with increasing spatial resolution. Also, automated *in situ* monitoring buoys enable the recording of continuous time series of SPM at specific sites for prolonged periods of time. These developments enable a new level of describing and understanding the physical and biological dynamics in coastal seas including SPM transport (see e.g. Robinson et al., 2002). Part of this development is the extended use of numerical transport models, as combining all these observational data resources enables the operational use of numerical models for various water quality applications. In recent years, integrated observation-modeling efforts have been and are undertaken to further describe and understand the North Sea SPM transport system exploiting the new sources of information available (e.g., Gerritsen et al. 2000, Eleveld et al., 2004, Gayer et al, 2006, De Boer et al, 2007, Allen et al, 2007, Fettweis et al, 2007).

The integrated approach aims to overcome the challenges met in both remote sensing and modeling when carried out separately. Derivation of accurate SPM values for this highly dynamic coastal sea where large-scale circulation, tidal currents and riverine fresh water inputs occur is notoriously difficult. SPM retrieval from ocean color remote sensing is dependent on good atmospheric correction, and characterisation of the high variability in Inherent Optical Properties (IOPs) in Case 2 waters. Modeling suffers from propagation of uncertainties in hydrodynamic forcing and SPM behavior, in addition to uncertainties in the parameterization of water-bed exchange of sand-mud mixtures.

In this paper we describe the combination of remotely sensed SPM and derived remote sensing products and an SPM transport model of the southern North Sea to support assessment of SPM conditions in the Dutch coastal zone. To this end, a generic data assimilation technique is applied, the Ensemble Kalman Filter (EnKF) as introduced by Evensen (1994) and described in Evensen (2003) is used to reduce the model errors and to significantly improve the accuracy of the predictions and operational forecasts.

This paper is part of a study that aims to increase our level of description and understanding of the coastal SPM transport with an application to support policy and decision making related to human interventions in the coastal system (such as infrastructure works, dredging and dumping etc.). Eventually, we wish to improve our means of detecting trends in SPM conditions and help distinguishing between natural and anthropogenic changes in the SPM (and eventually also in the ecosystem) in coastal waters. The objectives are to calculate fluxes of SPM and to obtain information in space and time including the vertical distribution of SPM over the entire Dutch coastal zone that are not available from measurements alone.

Particular challenges in remotely sensed nearshore SPM observations are encountered. The most prominent challenges are:

- 1) The large number of scatterers (high sediment load) near the coast causes reduction of optical depth, possibly saturation of the signal and might impede the atmospheric correction (Ruddick et al., 2000);
- 2) The number of observations per pixel vary due to cloudiness and MERIS Level 2 quality flag settings. In the mean time major changes in SPM concentrations between observations can occur (Fettweis et al., 2007), particularly by resuspension during windy conditions (Eleveld et al., 2004);
- 3) Remote sensing (RS) allows estimation of SPM over a top layer of the North Sea (optical depth), in a region where salinity stratification (De Boer et al., 2006) occurs, whereas the model solves the mass balance over the full water column in 10 layers varying with water depth and incorporates exchange with bed. Information on optical depth needs to be incorporated in the DA to eliminate or decrease any possible mismatch between observed SPM concentrations (and derived mass), and predicted mass for the corresponding depth layer.

This paper first presents the results of analysis of the MERIS SPM products retrieved by mean of the HYDROPT algorithm. Also, the opportunities that they offer for data assimilation are indicated. Secondly the model system will be described and results are discussed. Thirdly the approach towards and results of assimilating the model with the remotely sensed SPM products is presented. Finally a comparison against *in situ* data is presented.

2. Approach

The approach to make optimal use of remote sensing data, model applications and *in situ* data is outlined below in Figure 3. In the present study, the year 2003 serves as a test case. For this entire year, MERIS Reduced Resolution water leaving radiance data have been processed by VU-IVM, using the HYDROPT algorithm (Pasterkamp and Van der Woerd, 2007). As discussed also by Eleveld et al. (2007), these data have been extensively quality checked and various error products (in the scheme collectively indicated by σ_{SPM}) and the extinction coefficients (K_{d560}) have been determined and analyzed. These additional data products provide indispensable information for the data assimilation (see also El Serafy et al., 2007). The SPM and related data are used to continuously update the SPM transport model solution, hereby exploiting the now known uncertainties in the remotely sensed SPM data together with model uncertainties assessed from ensemble run experiments. Eventually, the assimilated model result of SPM concentrations (covering the entire year and extension over the vertical) and associated extinction coefficient will be compared against *in situ* field data from various sources to assess whether a closer description of the system is obtained. Finally, SPM transport fluxes may be determined from the model as well.

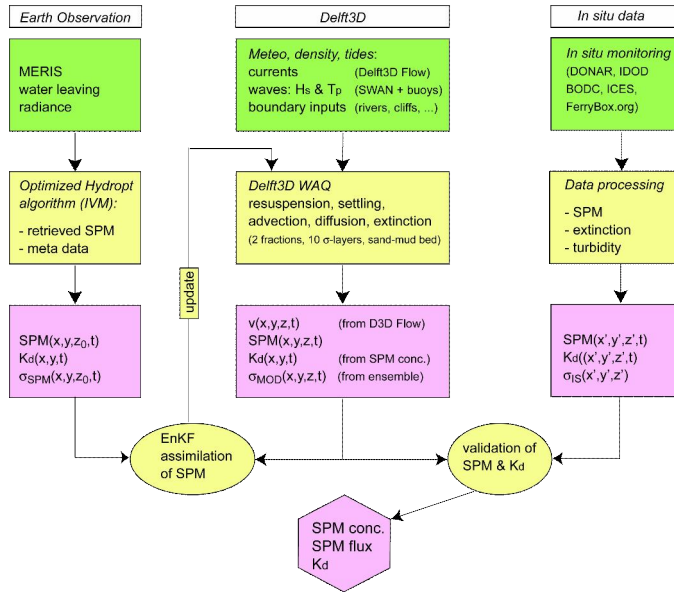


Figure 3. Scheme of the data-model integration applied to obtain improved accuracy data sets of SPM concentrations and associated fluxes and extinction coefficients.

3 Remote Sensing

3.1 Dataset for the data assimilation

The Medium Resolution Imaging Spectrometer instrument (MERIS) is an imaging spectrometer on board ESA's ENVISAT spacecraft. SPM in the North Sea was studied with MERIS RR MEGS 7.4 / IPF 5.03 atmospherically corrected (Level 2) data (ESA, 2007). All MERIS RR and selected MERIS FR data covering the North Sea for 2003 were acquired and all water pixels that pass the PCD1_13 confidence checking were processed using HYDROPT (Van der Woerd and Pasterkamp, 2007).

HYDROPT comprises of a forward model that generates water-leaving radiance reflectance (ρ_w) as a function of, a.o., the Inherent Optical Properties (IOPs) absorption (a) and scattering (b) of North Sea water and its constituents chlorophyll (CHL), SPM and colored dissolved organic matter (CDOM). It is based on radiative transfer modelling with Hydrolight (Mobley & Sundman, 2001a and b) REVAMP IOPs (Tilstone et al., submitted) weighted (by optimisation) with the annual mean of independently collected (MWTL) in situ concentration measurements for the Dutch coast (Rijkswaterstaat, 2007).

The inverse model estimates the concentrations of, a.o., SPM from MERIS water-leaving radiance reflectance ρ_w data at 7 optical wavelength intervals based on the Levenberg-Marquard optimization. The inversion comprises of χ^2 fitting the modelled to the measured water-leaving radiance reflectance, and also renders standard errors (σ) with the retrieved CHL, SPM and CDOM concentrations. In addition, probability was derived from the (cumulative) distribution function for the χ^2 distribution, and ESA's Level 2 Product Confidence Data (PCD) flags (ESA, 2007) were passed on (Van der Woerd and Pasterkamp, 2007).

Additional to modeled reflectance, complementary vertical diffuse attenuation coefficient (K_D) values were generated, and K_D at 560 nm, which inverse can serve as an approximation of optical depth.

3.2 Nearshore coastal quality checks

To support the DA process, quality checks were performed on selected near-coastal subsets from the Level 2 and its accompanying (HYDROPT-processed) Level 3 dataset.

- (1) Results of the ocean colour algorithm were validated by plotting SPM_{rs} and SPM_{is} against time (t) for all 19 coastal stations which range in distance from the coast from 2 to 235 km. Additionally, atmospheric parameters and HYDROPT SPM and error products were studied along a transect.
- (2) Rectified maps were subtracted to characterise spatio-temporal (ST) change between observations.
- (3) A first approximation of optical depth $\zeta = 1/K_{D560}$ was calculated.

3.3 HYDROPT SPM Products from MERIS

The following data were generated with remote sensing for the Ensemble Kalman Filtering toolbox:

- Metadata: extracted from filename, and additional Level 2 tot Level 3 processing lineage,
- primary products: lat, lon, SPM,
- error products: χ^2_{pw} , P (cdf χ^2), σ_{SPM} , Level-2 flags
- K_{D560}

Examples and nearshore characteristics of the data set are presented in the following sections.

(1) The influence of the large number of scatterers (high sediment load) near the coast on the atmospheric correction and ocean colour algorithm seems to have less impact than anticipated. In our experience SPM from remote sensing compares well with in situ SPM measurements (see e.g., Fig. 4). Underlying parameters versus distance to the coastline are shown in Figs 5 – 7. Atmospheric properties remain stable along the transect until 1 km from the first land-pixel (Fig. 5). Reflectance in the near-infrared (from about 780-1400 nm) is low over water because of high water absorption at these wavelength. Reflectance at 560 nm – which is very susceptible to SPM scattering and low to CHL and CDOM absorption (Eleveld et al., 2006) – is high in turbid regions (Fig. 4). Hydropt gives realistic SPM results offshore and nearshore, and the errors remain very reasonable nearshore (Fig. 8).

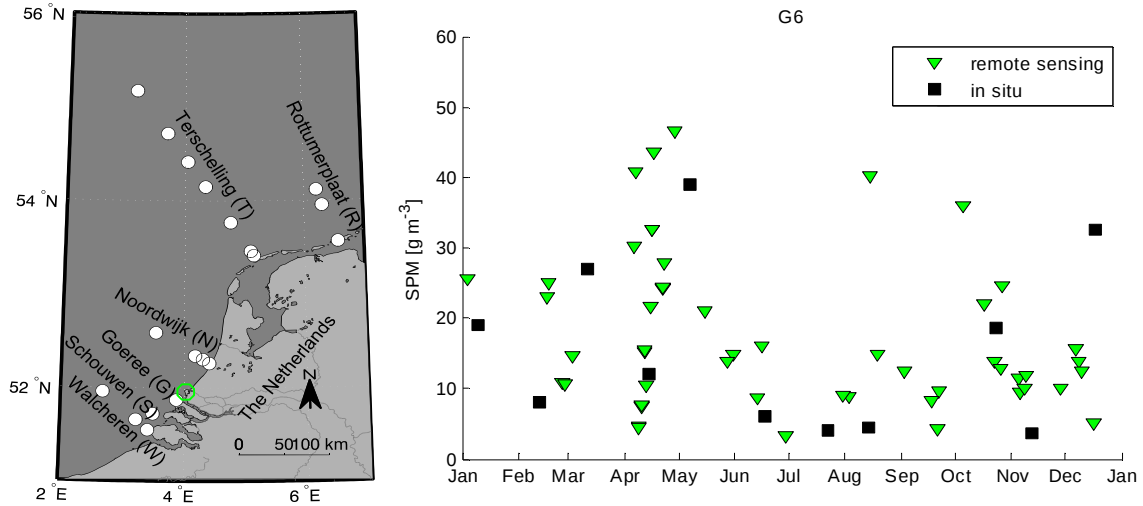


Figure 4 Comparison. The algorithm validates well for nearshore (2 km) and offshore (235 km) stations. Presented are results for station G6, which is located 6 km offshore near the dredging location for the extension of Rotterdam Harbour.

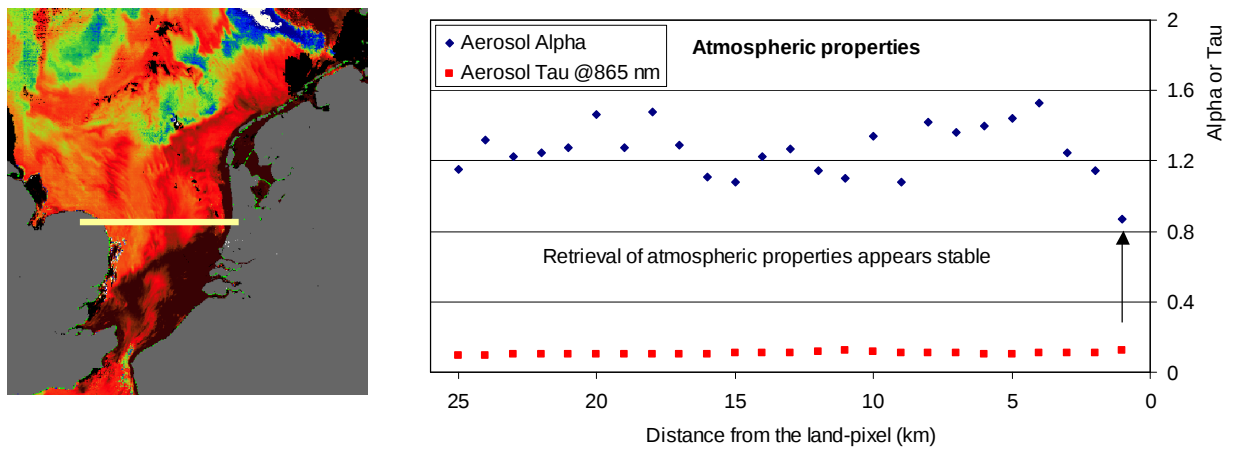


Figure 5 left: Transect on a MERIS Reduced resolution image of 16 April 2003; **right:** Atmospheric properties along the last 25 km of the transect approaching the Dutch coast. The aerosol optical depth at 865 nm varies offshore, but is considerably lower in the first km. Alpha, the baseline to estimate Tau for other wavelength is stable.

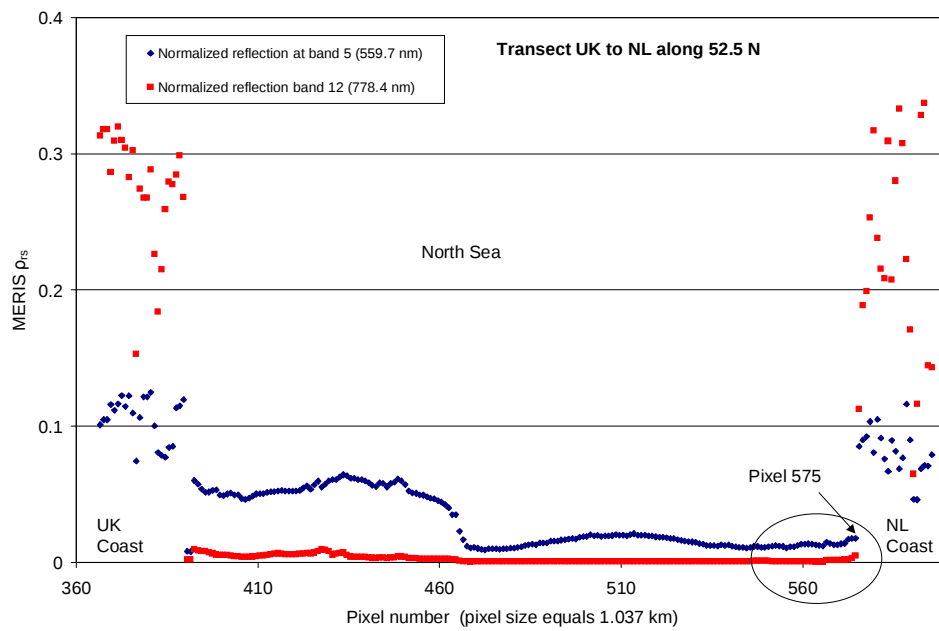


Figure 6 Reflectance along the transect at 560 nm (high SPM signal) and 778 (high water absorption).. Some problems in the atmospheric correction seem to occur in the first pixel classified as sea (pixel 575) in the Reduced Resolution data. For Full Resolution similar problems occur in the first kilometre (not presented).

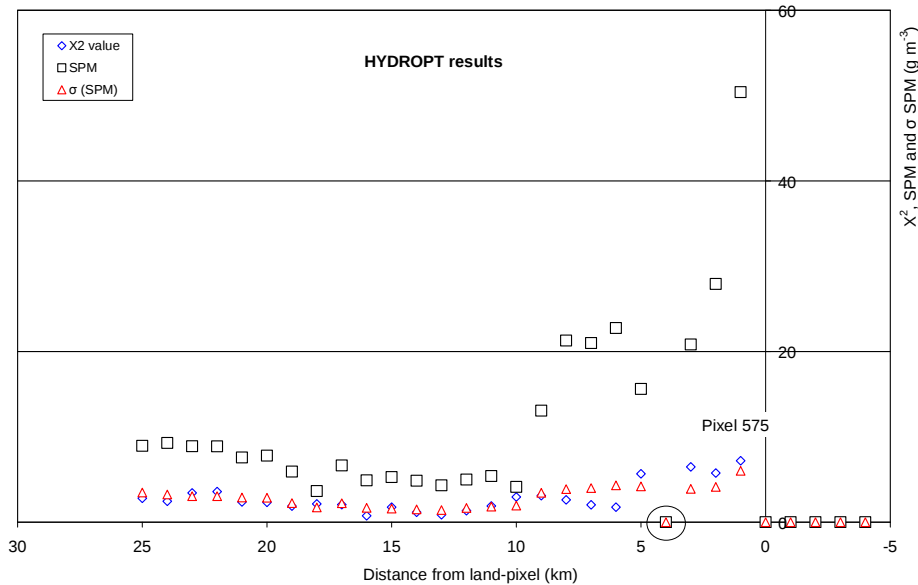


Figure 7 HYDROPT seems to perform robustly in the nearshore zone. Values for X^2 are not increasing much going landward. Minor changes in atmospheric parameters seem to be mitigated by the algorithm. Standard error σ is relatively low for high nearshore SPM concentrations. In some situations the algorithm produces 0-values.

(2) Figure 8 shows that important information about ST SPM change within a day can be derived despite exclusion of pixels due to local cloud cover and raised Product Confidence Flags (PCD1-13). Batch processing (Eleveld et al., 2003) allows fast processing of all data, making RS an important source of information, particularly because MERIS covers the area of interest once or twice a day.

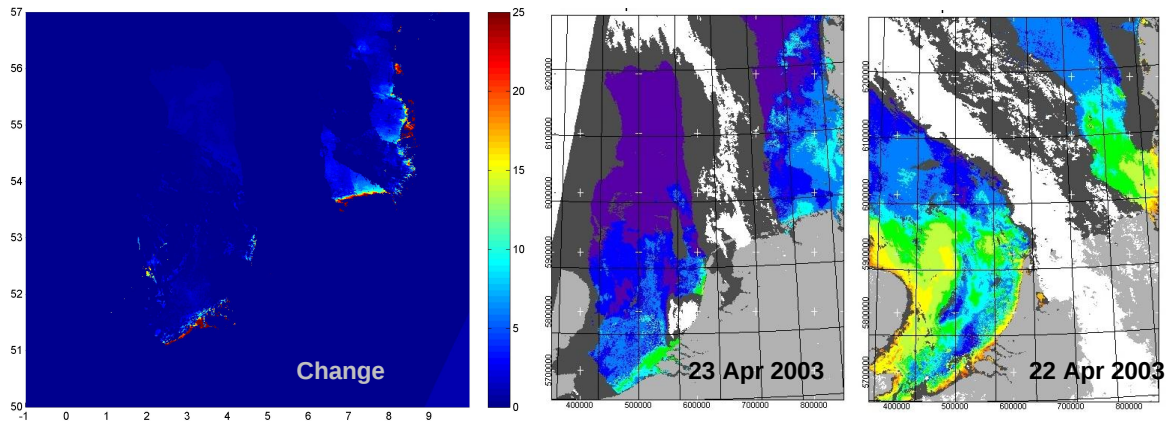


Figure 8 Remote sensing registers change between observations. (See Fig. 9 for legend April data.)

(3) Using HYDROPT to its full potential, concentrations of SPM and other optical substances (CHL, CDOM) have been retrieved from water-leaving radiance reflectance (ρ_w) of a top layer of the North Sea (optical depth). Independently of retrieved concentrations, K_D can also be derived in parallel with water-leaving radiance reflectance (ρ_w). Optical depth can be approximated by $1/K_{D560}$. Comparing independent panels in Fig. 8 shows that optical depth is low ≤ 1 m near shore, where many optically active substances reside, and higher 3-5 m near the turbidity minimum offshore. Providing optical depth for the DA enables best possible updating of model solution for this top layer.

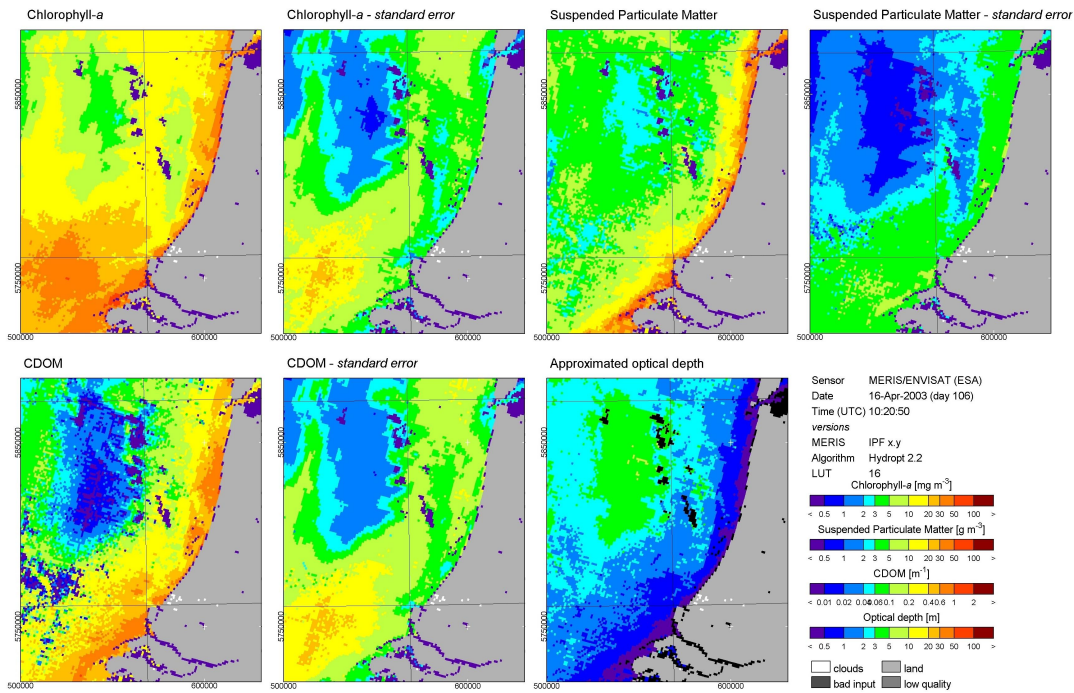


Figure 9 Water quality parameters and error products. Nearshore optical depth (approximated by $1/K_{D560}$) is limited.

4. The SPM Transport Model Description

The numerical model suite applied comprises the Delft3D Flow hydrodynamic model (Lesser et al, 2004), the surface wave model SWAN (Booij et al., 1999) and the sediment transport and water quality model Delft3D-WAQ (e.g., Van Gils et al. 1993, Los et al, 2006). These models are applied on a domain covering the southern North Sea (see Figure 10). The horizontal grid spans 65 columns x 134 rows. horizontal resolution is highest in the coastal areas of interest, notably the Dutch coastal zone (up to $\sim 2 \times 2$ km). The grid is coarser in the outer

parts of the area included in the model (down to $\sim 20 \times 20$ km). In the vertical 10 s-layers are applied. Near the bed and near the surface, the layer thickness is about 4 percent of the local water depth to enable good resolution of the surface mixing layer and the elevated near-bed SPM concentrations. At mid-depth, the layer thickness is approximately 20 percent of the local water depth.

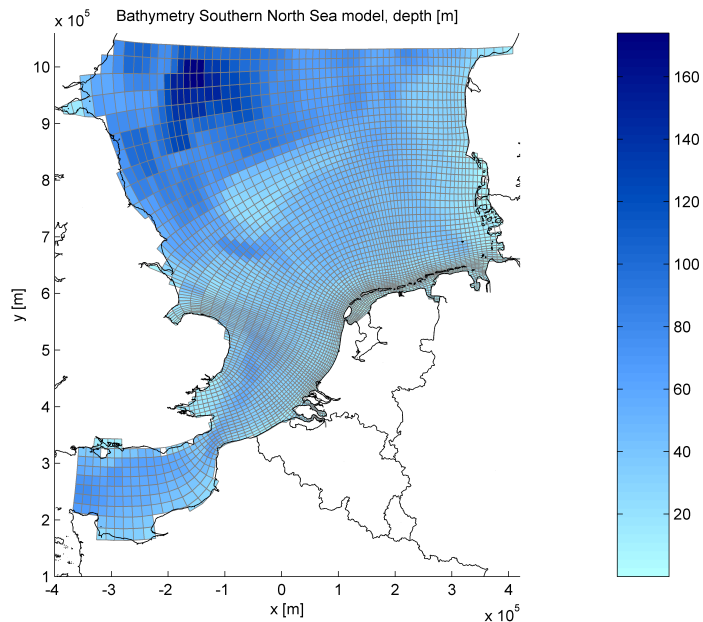


Figure 10. Horizontal grid of the Southern North Sea model applications, together with the bathymetry. The individual hydrodynamic, wave and transport models all operate on the same grid.

The water motion is governed by tidal, wind and density effects. Astronomic tides have been prescribed at the open boundaries. Atmospheric forcing has been derived from hindcasts of an limited area atmospheric model (HIRLAM, KNMI, see also <http://hirlam.org>). In addition, point sources where rivers discharge fresh water have been prescribed.

Resuspension due to surface waves, especially during strong wind events, is a key factor determining the SPM concentrations in the coastal seas. In order to obtain a model that describes the patterns of resuspension as accurate as possible given its resolution, appropriate wave height and period data are required as input. In order to achieve the desired accuracy, a data-model integration technique has been applied in which wave buoy observations are combined with the SWAN wave model results. The temporal evolution of the relevant wave parameters has been obtained from 6 wave buoys in the southern North Sea and the spatial interpolation is carried out with the aid of the spatial patterns in wave parameters derived from a SWAN wave model simulation for 2003. Figure 11 illustrates the spatial distance weight function and the annual mean significant wave height from SWAN.

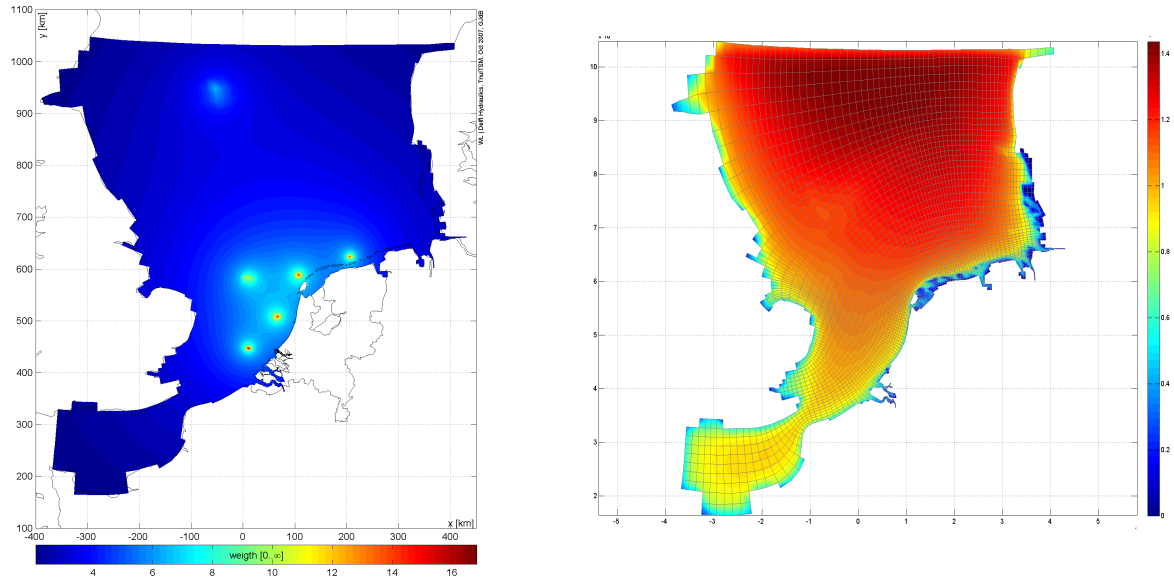


Figure 11 left: Spatial distance function related to the 6 wave buoy locations (local maxima);right annual mean significant wave height (m) for 2003 as determined by the wave model SWAN.

The sediment transport model Delft3D-WAQ computes the dispersion of suspended matter in two different silt fractions given the transport velocities, mixing coefficients and bed shear stresses adopted from the hydrodynamic and wave models. Recently, Delft3D-WAQ has been extended with an improved parameterization of the resuspension and buffering of silt fractions from and in a predominantly sandy seabed (Van Kessel et al., 2007). This parameterization enables a realistic description of the periodic and relatively limited resuspension during the tidal cycle and the massive resuspension from deeper bed layers observed during high wave events.

The transport model is provided with lateral boundary conditions based on climatological SPM concentrations, SPM loads from the rivers and specific point or line sources representing erosion of cliffs (e.g. off East Anglia) and the Flemish Banks. The model solution for 2003 is based on a multi-annual model experiment using water motion and wave information from 1996 onward. During the preparation of this experiment the solution, especially the slowly responding bed composition has been properly equilibrated.

5 Ensemble Kalman Filtering (EnKF)

5.1 Introduction

Hydrodynamic and transport models often contain several sources of uncertainty, which can occur at several stages during operation of the model. The governing equations may contain inaccuracies due to lack of knowledge about the complex physical processes and their interaction. Also, simplifications often must be made to avoid high computation times. These simplifications will increase the model's uncertainty. Uncertainties can also occur due to incorrect or incomplete input data of the model, such as boundary conditions, meteorological data, wave data and bathymetry. To reduce those uncertainties in the model output and improve its predictions, data assimilation techniques such as Kalman filter techniques can be applied. Those techniques combine the model forecast with recent measurement data, using the information on the uncertainties in the model and the measurements to give a better estimate of the model output. The Ensemble Kalman filter algorithm is here summarized as follows:

The sediment transport model propagates the system space state vector, SPM, in time. At initial time, t_k , an ensemble of size N is generated on the state vector. The ensemble is generated with a mean representing the initial condition of the state vector and with a covariance matrix that represents the uncertainty in the estimate of the initial condition. At every time step, t_k , each ensemble member, i , with its state vector forced by model errors

is propagated in time through the model. The model errors are randomly drawn from a predefined distribution with zero mean and a covariance matrix, Q_k . This covariance matrix represents the structure of the uncertainties in the model (also addressed as model errors). The estimate of the time update of the state vector can be calculated, at any time step, through the mean of the ensemble. The error covariance matrix in the estimate of the time update of the state vector, $P_{k|k-1}$, is calculated from the statistics of the ensemble. Moreover, random perturbations are added to the measurements. An ensemble of size N of possible observations is generated on the actual observations, using measurement errors. The measurement errors are also randomly generated from a predefined distribution with zero mean and covariance matrix, R_k , representing the uncertainties in the measurements or measurement errors. The Kalman gain matrix that acts as a weighting factor is then calculated using the measurement operator that maps the state vector to measurement domain. Finally, the state vector for every ensemble is then updated using the information on the uncertainties assumed. The full EnKF formulation is to be found in (Evensen 2003). The advantage of the ensemble Kalman filter is the feasibility of fast implementation in complex and high non-linear models. In this paper, the EnKF is applied to assimilate SPM Remote Sensing data in Delft3D-WAQ sediment transport model, where the uncertainties in both the model and observations and model are used to sequentially update the model.

5.2 Spatial Mapping

In order to assimilate the data into the model, spatial mapping has to be done to enable consistent comparison of two different domains (i.e. measured domain and modeled domain). Within the data assimilation technique, it is the model state that is normally mapped to the data. However, in the present application that would involve too many linear interpolations between the grid centers and the measured SPM at pixel level. This will introduce far too much complication in the data assimilation scheme. This might also lead to redundancy in the information, since two adjacent pixels most likely contain the same information. To avoid these complications, the data of the MERIS was mapped to model grid. There are several choices of mapping. The use of the error information in the averaging is most likely to be the best choice. For simplicity, a regular spatial averaging procedure was used as a first choice for the first tests of assimilation as here presented.

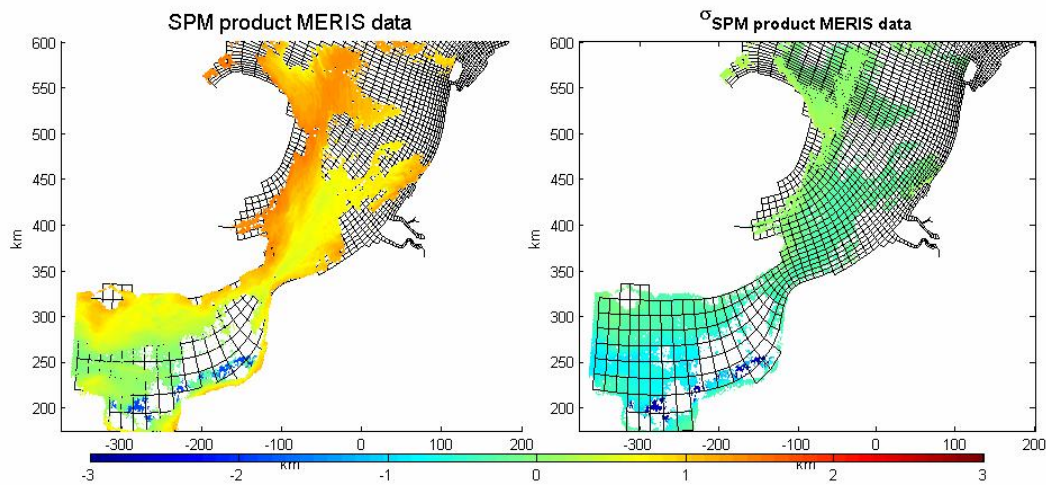


Figure 12 SPM product MERIS data and its standard deviation "zoomed" into the area of interest on the 17th December 2003 (Addressed in the text as RAW data)

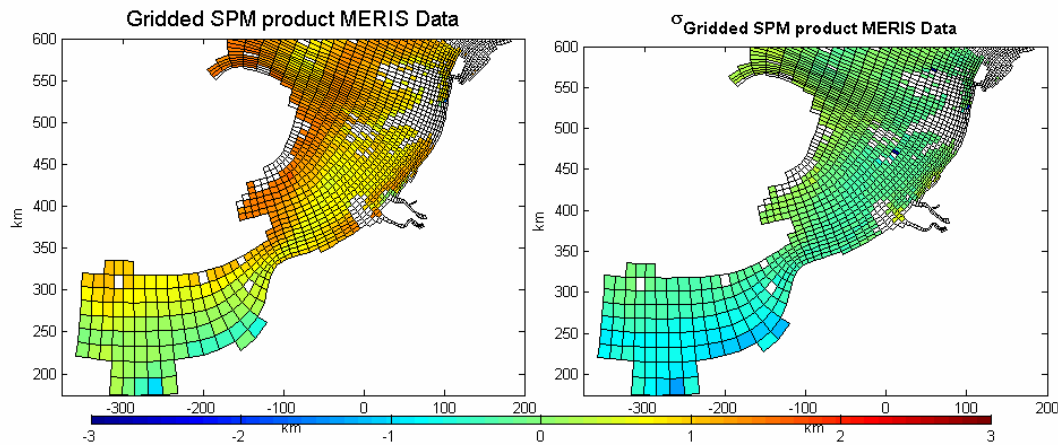


Figure 13 Gridded SPM product from MERIS data and the standard deviation of the gridded SPM on the 17th December 2003 used in the assimilation. Only the area of interest is shown in the figure.

In Figure 12 and 13, the difference between SPM product MERIS data (raw) and gridded data can be seen. From comparing the SPM shown in the figures, it is clear that all contained information in the pixel data is actually present in the gridded data. However, meanders and eddies resolved in the original, reduced resolution MERIS data are lost upon gridding. This indicates that a reasonable aggregation level has been achieved even with a simple spatial averaging procedure. However, when very few pixels are present within a grid cell of the model, some unrealistic results of SPM can be interpreted. By comparing the SPM product MERIS raw data (left panel of Figure) to the SPM gridded data (left panel of Figure) some unrealistic data coverage are present in the cloudy areas. This is due to the presence of one or two pixels in the grid cell. To avoid such artifacts, more sophisticated averaging including the number of pixels present in the cell, the error information and spatial interpolation would be recommended.

6 Assimilation Results

First results of the assimilation of MERIS-derived SPM into Delft3D-WAQ are encouraging. Updating of the model solution (state) has been carried out successfully. The SPM concentrations and error information have been gridded onto the computational grid of Delft3D WAQ. Consequently, an appropriate spatial aggregation level has been obtained, as it is not feasible and even undesirable to attempt to capture all individual small-scale structures due to eddies and meanders. Since remote sensing data are available nominally once (max twice) per day, the forward model integration between the updates provides a temporal and spatial interpolation on the appropriate scales.

A key aspect in the application of data assimilation is the use of known or assumed uncertainties or errors in both measurements and process model. The uncertainties in the measurements are provided as a measure of the retrieved value (i.e. standard deviation). The structure of the uncertainties in the model and typical correlation scales however is indirectly assumed based on the experience with the model itself during the calibration and validation of the model setup. For the water quality model (Delft3D-WAQ), the uncertainties are assigned only to the water column suspended particulate matter (i.e. independent variables in the filtering sense). The bed sediment load was considered to be a “certain” source and/or sink. At present, all other variables such as hydrodynamic variables and wave variables are considered to be considerably accurate driving forces for the sediment transport model and thus are not part of the state vector. It was also assumed that the observed SPM is equivalent to the modelled SPM within the surface layer of the model.

The experiment is carried out by assimilating the gridded SPM shown in Figure 14 into the model results on the 17th December 2003. An ensemble of only 30 members is used perturbed with the noise generated with the statistical assumptions made on the model error. It is assumed that the errors in the model are normally distributed with correlation scales of 100 km. The assimilated field is shown in the rightmost panel of Figure 14. From the figure it is seen that only slight improvements in the model results are obtained in the coarse resolution area due to the lack of information in this area. Deterioration has been also encountered in the SPM values in the open sea, presumably due to the large assumed correlation scales. Noticeable improvements are observed along

the Dutch coast, the high SPM values are improved to resemble those monitored by MERIS. Though the improvements in the model prediction appear not remarkably large, the results are very encouraging as a first preliminary results of the research, since they do point out the steps for future improvements. They also agree with sound reasonable explanations the results.

For example, having the correlation scales assumed to be 100 km might be considered a too high correlation scale of errors. The assumptions on the uncertainty structure of the model errors are to be considered as rough first estimates. Uncertainty analysis should be thoroughly carried out as a follow up. It is expected that this will enhance the results of the assimilation. Comparison of assimilation results due to different assumptions is also recommended as a verification step for the assumption on the uncertainties structure.

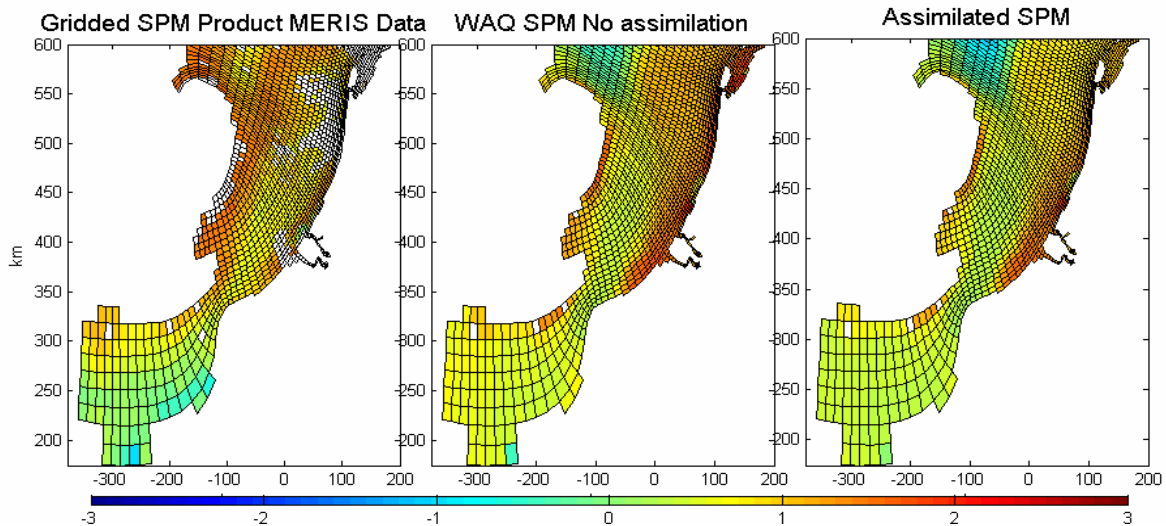


Figure 14 Gridded SPM Product of MERIS (left), Delft3D-WAQ predicted SPM without any assimilation (middle) and the SPM Estimate due to assimilation (right) on the 17th December 2003.

Moreover, the remote sensing data is observed from space and is limited to the surface layer (i.e. within the visible depth of the instrument) while the numerical model deals with the suspended particulate matter concentration within the upper sigma layers of variable depth. The water quality model also has a physical visible depth based on the concentration predicted. To be able to compare and/or to assimilate the observed SPM concentration into the model, one has to calculate and use the equivalent depths. In this experiment, this was not taken into consideration, only the first sigma layer of the model is assumed to be the optical depth observed. In other word, it is thus assumed that the SPM concentration observed by the instrument is equivalent to the predicted SPM concentration by the numerical model in the surface layer of the model. This can create horizontally inconsistent mismatch between the observation SPM mass within the visible depth and that of the model within the corresponding depth. Optical depth information needs to be incorporated in the assimilation to eliminate and/or decrease this mismatch.

Finally, the results here shown are a one-time assimilation at an individual date. By incorporating more data every day, the difference between the model SPM prediction and the observed data will decrease resulting in a better results of the EnKF. In other words, there is no prior information in the ensemble through the propagation of errors of the model in time at first applications, except the prior on initial conditions. It is expected that the EnKF results improve by incorporating measurements in time.

It has to be emphasized that the results here are preliminary results and will be improved by taking into consideration those aspects mentioned such as corresponding observed optical depth to the optical (visible depth) for the model, other averaging procedure including error information, and the assimilation of data for a period of time longer than one day.

7 Conclusions

Remotely sensed near-shore SPM with error products and K_D will be a valuable source for Ensemble Kalman Filtering because:

- Remotely sensed SPM results validate well with in situ data;
- Many SPM changes can be characterized with RS;
- Approximated optical depth can be delivered with the water quality parameters and their error product.

In this paper, the deterministic DELFT3D-WAQ sediment transport and water quality model is extended with an Ensemble Kalman filter (EnKF) technique that enables assimilation of recent observational data of different nature one of which is the remote sensing data from the MERIS imaging spectrometer. This improves the forecasting capability of the SPM predicting system. The techniques are demonstrated for SPM prediction in the southern North sea. From the first results, it is concluded that the assimilation of MERIS-derived SPM into a sediment transport model is technically feasible. It improves the prediction of the concentration distribution. Many new aspects related to the assimilation of SPM remote sensing data in numerical models such as the spatial mapping, the uncertainty definition, the definition of the optical depth, is identified during this research. Those issues have to be included as improvements in the present system.

The use of satellite optical depth information should be included in the assimilation scheme to eliminate any possible inconsistency between the observation SPM mass within the visible depth and that of the model within the corresponding depth. Moreover, applying physical constraints on the updated vertical distribution of suspended particulate matter (SPM concentrations) can be investigated. To be able to assimilate the remote sensing data into a numerical model, a special type of aggregation or spatial mapping is required. Mapping of the remote sensing data to model grid and vice versa to include error information and spatial interpolation is recommended. Finally, since the assumption on the uncertainty structure of the model errors used here are rough first estimates, more thorough uncertainty analysis should be carried out as a follow up. This would enhance the results of the assimilation. Comparison of assimilation results due to different assumptions is also recommended as a verification step for the assumption on the uncertainties structure.

From the experiments discussed here, we conclude that assimilation of MERIS derived SPM into a sediment transport model is technically feasible. Thanks to the additional error information on the remote sensing data, the EnKF can be successfully applied. The procedure seems suited to reach a solution that is consistent not only with the model equations, but also with general notions of the coastal system. Using a 3D transport model enables the interpolation in horizontal (underneath clouds) and time (between overpasses) as well as extrapolation over the vertical into the unobserved subsurface.

Applying this type of data assimilation for an entire year or even multiple years will extend the description of the coastal system in a physically consistent way suitable for baseline determination. Nevertheless, there are uncertainties and challenges to be dealt with: remote sensing is limited to the surface layer, whereas the bulk of the sediment is often found near the bed. This source of uncertainty will be attempted to be minimized by applying additional information on the optical depth and as such control an extended part of the model solution. This will eliminate any possible mismatch between the observed and modeled SPM mass within the visible depth interval.

A final step is objective quantitative assessment of the improvements obtained by application of the data assimilation. For this, we plan to adopt the method presented by Taylor (2001) who devised an objective measure for model skill depending on standard deviations of model and validation data, model-data correlation coefficient and the maximum potentially achievable correlation given the stochastic nature of the solution. Since the spatio-temporal scales of SPM in the coastal zone vary widely and stochastic patterns may be found that can only partly be resolved by the numerical models, a limit is to be expected as to what goodness of fit is achievable at all. In order to fully assess the value of the data-assimilation as described above, a follow-up study is recommended in which the 2007 conditions are to be simulated and validated against field data recently and currently collected by the Port of Rotterdam.

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References

- Allen, J.I., Holt J.T., Blackford, J. and Proctor, R., (2007), Error quantification of a high-resolution coupled hydrodynamic ecosystem coastal-ocean model: Part 2. Chlorophyll-a, nutrients and SPM, *J. Mar. Sys. (in press)*, doi:10.1016/j.jmarsys.2007.01.005
- Booij, N. Ris, R.C., Holthuijsen, L.H. (1999) A third-generation wave model for coastal regions 1: Model description and validation. *J. Geophys. Res.*, **104**(C4), pp. 7649–7666, april 15, 1999
- De Boer, G.J. Pietrzak, J.D., Winterwerp J.C., (2007), SST observations of upwelling induced by tidal straining in the Rhine ROFI, *Cont.Shelf Res. (in press)*, 2007.
- De Boer, G.J., Pietrzak, J.D., Winterwerp, J.C. (2006) On the vertical structure of the Rhine region of freshwater influence. *Ocean Dynamics* **56**, 198-216. DOI 10.1007/s10236-005-0042-1
- El Serafy, G.Y.H., Blaas, M., Eleveld, M.A., Van der Woerd, (2007). Data assimilation of satellite data of Suspended Particulate Matter in Delft3D-Delwaq for the North Sea. *Proceedings of the Joint 2007 EUMETSAT/AMS Conference*.
- Eleveld, M.A., Pasterkamp, R., van der Woerd, H.J. (2004) A survey of total suspended matter in the southern North Sea based on the 2001 SeaWiFS data. *EARSeL eProceeding* **3**(2), 166-178. URL: <http://www.e proceedings.org/>
- Eleveld, M.A., Pasterkamp, R., van der Woerd, H.J., Pietrzak, J. (2006). Suspended particulate matter from SeaWiFS data: statistical validation, and verification against the physical oceanography of the southern North Sea. *Ocean Optics OOXVIII*, (9-14 Oct. 2006, Montreal). Publisher: Lewis Conference Services International Inc., Halifax (Ca), 60234, 18 pp.
- Eleveld, M.A., Van der Woerd, H.J, Blaas, M., El Serafy, G.Y.H. (2007), Using SPM observations derived from MERIS reflectances in a data assimilation scheme for sediment transport in the Dutch coastal zone. *Proceedings of the Joint 2007 EUMETSAT/AMS Conference*.
- Eleveld, M.A., Wagtendonk, A.J., Pasterkamp, R. & Omtzigt, A.Q.A., (2003). Monitoring North Sea coastal waters: from radiance at sensor data to a Web mapping service. Genova, Italy, *Proceedings CoastGIS 2003, Fifth International Symposium on GIS and Computer Cartography for Coastal Zone Management*, 9 pp. (CD & URL: <http://www.gisig.it/coastgis/>)
- ESA (2006) MERIS Product handbook. Issue 2.0 (14 Apr 2006). <http://envisat.esa.int/handbooks/meris/>
- Evensen G. (1994a). "Sequential data Assimilation with Non-Linear quasi-geotropic model using Monte Carlo methods to forecast error statistics," *J. Geophys. Res. Oceans*, 99(C5), pp. 10143-102.
- Evensen G. (2003) The Ensemble Kalman Filter: theoretical formulation and practical implementation, *Ocean Dynamics* (2003) **53**: 343–367.
- Fettweis, M., Nechad, B., Van den Eynde, D. (2007). An estimate of the suspended particulate matter (SPM) transport in the southern North Sea using SeaWiFS images, in situ measurements and numerical model results. *Cont. Shelf Res.* **27**, pp. 1568–1583.
- Gayer, G., Dick, S., Pleskachevsky, A., Rosenthal, W. (2006) Numerical modelling of suspended matter transport in the North Sea. *Ocean Dyn.* **56**: 62-77. DOI 10.1007/s10236-006-0070-5
- Gerritsen H.G., Vos, R.J., Van der Kaaij, Th., Lane, A., Boon, J.G., (2000) Suspended sediment modelling in a shelf sea (North Sea). *Coastal Engineering* **41**, pp. 317-352.
- Gordon, H.R., Brown, O.B., Jacobs, M.M. (1975) Computed relationships between the inherent and apparent optical properties of a flat homogeneous ocean. *Applied Optics* **14**, 417-427.
- Lesser G.R., Roelvink J.A., van Kester J. A.T. M. and Stelling, G. S. (2004). "Development and validation of a three-dimensional morphological model," *Coastal Engineering* **51**(8-9), pp. 883-915.
- Los, F.J., Tatman, S., Minns, A.W. (2004) Flyland - A Future Airport in the North Sea? An Integrated Modelling Approach for Marine Ecology, *6th International Conference on Hydroinformatics* - Liong, Phoon & Babovic (eds) World

- Scientific 2004, ISBN 981-238-787-0.
- Mobley, C.D., Sundman, L.K. (2001b) *Hydrolight 4.2: Users' guide*. (Sec. printing, Oct. 2001). Sequoia Scientific, Redmond (WA) USA, 88 pp. <http://www.sequoiasci.com/products/Hydrolight.aspx>
- Pasterkamp, R., van der Woerd, H.J. (2007) HYDROPT: A fast and flexible method to retrieve chlorophyll-a from multi-spectral satellite observation of optical-complex coastal waters. *Accepted by R.S. Env.*
- Press, W.H., Vetterling, W.T., Teukolsky, S.A., Flannery, B.R. (1992) *Numerical recipes in Fortran: The art of scientific computing*. Sec. Ed. Ch. 15: Modelling of data. Cambridge University Press: New York, pp. 650-700
- Rijkswaterstaat (2007) Waterbase. <http://www.waterbase.nl>
- Robinson, A.R., and Lermusiaux, P.F.J. (2002), Data assimilation for modelling and predicting coupled physical-biological interactions in the sea. In: *The Sea*, Vol 12. Ed. A.R. Robinson, J.J. McCarthy, and B.J. Rothschild. Wiley, New York.
- Ruddick, K., Ovidio, F., Rijkeboer, M., (2000) Atmospheric correction of SeaWiFS imagery for turbid coastal and inland waters. *Applied Optics* **39**(6), pp. 897 - 912.
- Taylor, K.E. (2001), Summarizing multiple aspects of model performance in a single diagram, *J. Geophys. Res.* **106**(D7), 7183--7192
- Tilstone, G., van der Woerd, H., Krasemann, H., Martinez-Vicente, V., Aas, E., Blondeau-Patissier, D., Doerffer, R., Eleveld, M., Hokedal, J., Jorgensen, P., Pasterkamp, R., Peters, S., Rottgers R., Ruddick, K., Schoenfeld, W., Sorensen, K. (submitted) Regional variation in the inherent optical properties of the North Sea: Application to ocean colour satellite algorithms. *Submitted to J. Geophys. Res.*
- Van der Woerd, H.J., Pasterkamp, R., (2007) HYDROPT: A fast and flexible method to retrieve chlorophyll-a from multispectral satellite observations of optically complex coastal waters. *Accepted by R.S. Env.*
- Van der Woerd, H.J., Pasterkamp, R., Peters, S.W.M., Eleveld, M.A. (2004) How to deal with spatial variability in bio-optical properties in coastal waters: a case study of CHL-retrieval for the North Sea. *Ocean Optics* XVII (25-29 Oct. 2004, Fremantle). Publisher: Lewis Conference Services International Inc., Halifax (Ca), (OOXVII-2-184), 10 pp.
- Van Gils, J.A.G., Ouboter M.R.L., De Rooij M.N. (1993) Modelling of water and sediment quality in the Scheldt Estuary, *Neth J. Aq. Ecol.* **27**(2-4), 257-265, 1996.
- Van Kessel, T., Winterwerp J.C., Van Prooijen, B.C., Van Ledden, M., and Borst, W.G., (2007) Modelling theseasonal dynamics of SPM with a simple algorithm for the buffering of fines in a sandy seabed. *Proceedings of INTERCOH'07 Brest France*, 2007
- Vos, R.J. Ten Brummelhuis, P.J.G., Gerritsen, H., (2000). Integrated data-modelling approach for suspended sediment transport on a regional scale. *Coastal Engineering* **41**, pp. 177–200.
- Winterwerp, J.C., Van Kesteren, W.G.M. (2004) Introduction to the physics of cohesive sediment in the marine environment. *Developments in sedimentology* 56, (Elsevier, Amsterdam).