TnulTSM

Integration of remote sensing and modelling of suspended matter in the Dutch coastal zone

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Report

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Abstract

Suspended particulate matter (SPM) is an important water quality parameter in Dutch coastal waters. Accurate monitoring of SPM distributions and transports is essential for Environmental Impact Assessments (EIA) related to large-scale interferences in the coastal system. One such interference is the extension of the Maasvlakte land reclamation at the Port of Rotterdam. Within the context of the EIA, baseline conditions and possible future changes in SPM have to be assessed, whereas the dynamics of the system are strong and current insights are limited.

In this project we demonstrate the feasibility of combining remote sensing products and simulation modelling of SPM through data assimilation in order to improve SPM monitoring in coastal waters. *In situ* measurements have been used for validation and skill assessment of the assimilated model. The assimilation was setup and tested for a baseline study, with particular application to the year 2003. With the aid of the Hydropt algorithm, SPM concentrations have been retrieved from MERIS Reduced Resolution data, together with an extensive meta-data set. These data have been assimilated in the Delft3D sediment transport model of the southern North Sea using Ensemble Kalman Filtering (EnKF).

The project has shown that the remote sensing and transport model are of sufficiently good quality to facilitate assimilation. The EnKF has resulted in a stable reanalysis of the surface concentrations. This reanalysis is an improved data product in the sense that (1) it is closer to the validation data than the results of a model without assimilation and (2) it provides continuous information in time and space where remote sensing and *in situ* observations do not. From the assimilation, additional insight in remote sensing and modelling of SPM in the Dutch coastal waters is gained as well.

A user requirement analysis and a cost-benefit analysis have also been part of the project. The innovations achieved prepare the road for future operational applications, which will be of interest for various public and commercial parties involved in coastal management and infrastructure development.

References	

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NATIONAL USER SUPPORT PROGRAMME (NUSP) 2001-2005

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The National User Support Programme 2001-2005 (NUSP) is executed by the Netherlands Agency for Aerospace Programmes (NIVR) and the SRON Netherlands Institute for Space Research. The NUSP is financed from the national space budget. The NUSP subsidy arrangement contributes to the development of new applications and policy-supporting research, institutional use and use by private companies.

The objectives of the NUSP are:

- To support those in the Netherlands, who are users of information from existing and future European and non-European earth observation systems in the development of new applications for scientific research, industrial and policy research and operational use;

- To stimulate the (inter)national service market based on space-based derived operational geo-information products by means of strengthening the position of the Dutch private service sector;

- To assist in the development of a national Geo-spatial data and information infrastructure, in association with European and non-European infrastructures, based on Dutch user needs;

- To supply information to the general public on national and international space-based geo-information applications, new developments and scientific research results.

vrije **Universiteit** ***amsterdam / IVM***

The Remote Sensing group at the Institute for Environmental Studies (IVM) of the *Vrije Universiteit* (VU) Amsterdam has about 20 years of experience in remote sensing of complex (Case 2) waters. The Remote Sensing Group at VU-IVM in particular focuses on collection of Concentration, Spectra and Inherent optical properties (CSI) datasets, bio-optical forward and inverse modelling, algorithm development and validation. IVM uses physics (optics) to derive water quality parameters from remote sensing, and specialises in remote sensing of turbid and eutrophic waters. Throughout the years many of IVM's projects have focussed on the North Sea and the Lake IJssel area.

For more information see http://www.ivm.vu.nl

Deltares
Enabling Delta Life

Deltares is a newly formed technological institute based in Delft and Utrecht. It merges the former WL | Delft Hydraulics, GeoDelft, the Subsurface and Groundwater unit of TNO and parts of Rijkswater-staat RIKZ & RIZA. Deltares combines the development, distribution and application of knowledge in the fields of surface water and groundwater, the subsurface, water and soil quality, and spatial planning. Deltares has over 15 years of experience with the integration of surface-water quality modelling and observational data.

For more information see http://www.deltares.nl

Executive summary

Introduction

Suspended particulate matter (SPM) is an important water quality parameter in Dutch coastal waters. Accurate monitoring of SPM distributions and transports is essential for Environmental Impact Assessments (EIA) related to large-scale interferences in the coastal system. One such interference is the extension of the Maasvlakte land reclamation at the Port of Rotterdam.

For this land reclamation an extensive sand mining operation is scheduled which may induce undesired elevated SPM concentrations in the coastal zone. The relevance of these enhanced concentrations is mostly in the effect they may have on the underwater light conditions. Light is the dominant steering factor in the growth of algae which are at the base of the marine food web.

Within the context of the EIA, baseline conditions and possible future changes in SPM have to be assessed. Because the baseline conditions are poorly known and highly variable and because the expected possible changes that are deemed relevant or relatively small, a monitoring strategy is required that has sufficient power to distinguish the effects from noise. Preferably a monitoring strategy is applied that not only enables detection of presence of absence of trends in the conditions but also aids identifying the cause if any trend would be detected.

Objectives

In order to meet these needs the project TnuITSM aimed to develop a more accurate and cost effective model-supported monitoring technique by

- Application and refining of existing techniques of data assimilation in a combination of SPM modeling, remote sensing and *in situ* observations.
- Investigating the technical and economic feasibility of implementation of the techniques in an operational system

The application will eventually provide monitoring instruments that yield more extensive and accurate information on concentrations and fluxes of SPM than can be achieved by means of the individual sources of information separately. This data-model integration could be referred to as ‘model-supported monitoring’.

Approach

The project relied on three sources of information, remote sensing, modelling and in situ observations. The integration of remote sensing products and simulation modelling of SPM is achieved through data assimilation using Ensemble Kalman FIltering (EnKF). *In situ* measurements have been used for validation and skill assessment of the assimilated model.

Remote sensing data of SPM have been retrieved from the MERIS sensor on the ESA ENVISAT-satellite. With the aid of the Hydropt algorithm, SPM concentrations have been retrieved from MERIS Reduced Resolution data, together with an extensive meta-data set.

The models comprise the Delft3D modelling suite for hydrodynamics, waves, and sediment transport of the Southern North Sea. The *in situ* data have been obtained from national monitoring programs.

The assimilation was setup and tested for a baseline study, with particular application to the year 2003. In the verification and validation objective measures for Goodness of Fit have been applied.

Results

The project has shown that the remote sensing and transport model are of sufficiently good quality to facilitate assimilation.

The Hydropt algorithm performs well for SPM in the Dutch coastal region. The remote sensing SPM retrieval algorithm also provides error products and information on extinction of visible light. This study also shown that Hydropt performs well for use within the first few kilometres offshore, which traditionally is considered a challenge.

The EnKF has resulted in a stable and mostly sensible reanalysis of the surface concentrations. Specific issues rise related to applicability of both the optical and transport model in the central North Sea. And within the coastal zone, effects of a long term bias between model and remote sensing are visible, in particular in periods of enhanced vertical mixing after periods of stratification.
Nevertheless, the reanalysis is an improved data product in the sense that

- it is closer to the validation data than the results of a model without assimilation;
- it provides continuous information in time and space where remote sensing and *in situ* observations do not;
- additional insight in remote sensing and modelling of SPM in the Dutch coastal waters is gained.

After assimilation, the model has gained skill in describing both the annual mean and seasonal variations. The skill is in between that of the deterministic model and the MERIS data. Assessment of skill is however limited to only those instances and scales that are resolved by the validation data. Future activities are foreseen to elaborate on these aspects.

SWOT Analysis

An analysis of the Strengths, Weaknesses, Opportunities and Threats (SWOT) has been made of the envisioned model-supported monitoring system in conjunction with an inventory of costs and benefits

Strengths relate mostly to the fact that complementary data sources are used such that information becomes available on a daily basis covering a large spatial area. The model enables to overcome some of the traditional drawbacks of remote sensing and *in situ* data interpolation in time and space and extrapolation over the entire water column. In addition the models provide insight in sources and sinks of SPM. The techniques that are generic and can be used for other applications and areas.

Weakness relates to technical challenges ahead such as further refinement of optical and numerical models, validation and dependence on data dissemination infrastructures.

Opportunities are increasing acceptance of remote sensing as a robust source of monitoring information. Information technology and developments of sensors make integrated monitoring and information systems more desired and affordable. Also, nationally and internationally driven reconsiderations of monitoring strategies offer opportunities. Various concrete projects nationally and abroad are in need for means of integrated monitoring.

Threats are mostly in the domain of perception and acceptance due to lack of awareness, training or internal interests. Also decommissioning in case of dependence on too few sensors may be a threat.

Cost Benefit Analysis

Benefits of a model-supported monitoring system integrating remote sensing, in situ and numerical models are related to the combination of complementary data sources. Gaps can be bridged and predictions can be made. Additional insight in sources and sinks is obtained and cause effect relations also to other compartments of the ecosystem are facilitated. A model-supported strategy is likely to have more distinctive power than a method relying on only one component. This leads to clearer answers, less uncertain decisions at reduced monitoring efforts.

Concrete costing in terms of the expected value depend on the power of a strategy and the consequences of not having certain power. Moreover, the perception of uncertainty and costs related to that by decision makers plays an important role. This appeared to be nontrivial and requires additional research in future. For the current context, conservative assumptions have been made.

The costs of developing and operating a model-supported monitoring system have been inventoried along with the costs of a conventional ship-based monitoring programme in the context of the Port of Rotterdam. For the sake of the argument it has been assumed that ship-based monitoring can achieve comparable power as the model-supported approach.

The conclusion is that one-off investments for model-supported monitoring are about five times higher than ship-based monitoring, but that annual operational costs for model-supported monitoring are less than half the operational costs of ship-based monitoring. Under those provisions, a combination of ship-based monitoring and model-supported monitoring is more cost effective as soon as one can reduce the annual ship costs by a factor of about 2.5 while retaining the same power. It should be kept in mind dat also for a model-supported monitoring porgramme, at least limited ship based monitoring remains essential.

Outlook

Future developments will be partly focused around the interests of the Port of Rotterdam. The Port of Rotterdam is aiming for an operational model-supported

monitoring system that relies on regular retrieval of SPM from Remote Sensing with occasional ship surveys and the possibility to connect to forecasts and cause-effect studies in the ecosystem. A follow up project is being prepared that will take the developments of TnuITSM further towards operationalisation.
Nevertheless more opportunities are expected. Since the techniques are generic they can be applied in different regions and scales as well. Hence, the innovations achieved prepare the road for future operational applications, which will be of interest for various public and commercial parties involved in coastal management and infrastructure development.

Contents

1 Introduction and objectives

1.1 Project context

This report presents the results of a research project jointly carried out by Deltares (former WL | Delft Hydraulics) and VU-IVM (Institute for Environmental Studies, *Vrije Universiteit Amsterdam*) between autumn 2006 and spring 2008. This project, ‘TnulTSM’, has been subsidised by the Dutch National User Support Programme (‘GO’) under the auspices of the Netherlands Agency for Aerospace Programmes (NIVR). TnulTSM aimed at demonstrating the feasibility and benefits of the combined use of remote sensing and numerical modelling of suspended matter in coastal waters. The integration of these data sources can be applied to supplement *in situ* monitoring of suspended matter to obtain more complete and accurate information of the coastal sediment transport system.

Accurate monitoring of suspended matter is not only helpful for furthering our insights in the coastal system, it is also essential in the context of compliance with national and international laws and directives on surface water quality. It is therefore noteworthy that the project has been completed in close collaboration with the Port of Rotterdam, who is one of the possible future end-users interested in applying the techniques that have been developed within TnulTSM for monitoring purposes.

From a historic perspective, it is remarked that WL | Delft Hydraulics and VU-IVM have an extensive track record, not only on modelling and remote sensing of suspended matter but also on integration of these. In the 1990s the project RestWaq (Vos and Schuttelaar, 1995) applied NOAA/AVHRR reflectance data as a source of information for rescaling the modelled mass of SPM. In the late 1990s the project RESTWES (Villars and Vos, 1999) applied remote sensing in an integrated monitoring tool for the Western Scheldt. Later, the more extensive variational approach was explored by Gerritsen *et al.* (2000) and Vos *et al.* (2000). The use of SeaWiFS data in combination with transport models has also been investigated (e.g, Villars et al. 2002). Most recently, Deltares and partners developed a tool to support dredging operations using transport models and remote sensing of suspended matter within the NIVR User Support project RESTSCOD (Tatman et al, 2005, 2007, Tatman 2005)
These projects have built valuable experience that enabled both Deltares and IVM to achieve the current innovations.

1.2 SPM in the coastal zone

Suspended particulate matter (SPM, also referred to as Total Suspended Matter, TSM) consists of silt and particulate organic material. SPM is an important environmental parameter in the Dutch Coastal zone. The concentration levels of SPM determine the underwater light conditions, which influence the primary production by phytoplankton in the coastal waters. Organic content of SPM is also an important food source at the basis of the food web, and (changes in) SPM may affect the foraging of juvenile fish and the visibility of prey for certain birds in the coastal zone. Finally, fluxes of SPM between the Dutch North Sea coastal waters and the Wadden Sea are considered to be important for the marine environment of the Wadden Sea (nutrient inputs and bed-sediment composition).

SPM is a natural constituent of the coastal waters and as such affects the color of the sea. As a consequence, SPM can be observed by air- or spaceborne optical sensors. Figure 1 illustrates the coloring of the waters of the southern North Sea due to suspended and dissolved matter as observed by the MODIS sensor aboard the Terra platform.

Figure 1.1 True colour image of the southern North Sea showing contrasts in sea water color due to suspended and dissolved matter. MODIS (Terra) recording, March 26, 2007. (Image courtesy of MODIS Rapid Response Project NASA/GSFC).

SPM in the coastal zone is partly originating directly from rivers and coastal erosion, but the majority is being exchanged between the sea floor and water column. Certain geographic areas such as the Flemish Banks are localised sources of suspended matter, but also the silt present in the predominantly sandy seabed elsewhere is redelivered to the water column during times of resuspension. Natural resuspension is caused by strong near-bed currents due to tides and, mostly, due to the effect of waves during strong wind conditions. For more extensive information on SPM transport in the Dutch coastal zone we refer to Eisma (1981), Van Alphen (1990), Jones et al. (1998), Fettweis & Van den Eynde (2003) and Winterwerp (2006), for example.

SPM can be released from the sea floor not only due to these natural processes, but also due to human activities, such as large-scale sand mining activities required for land reclamation and large-scale beach nourishment. In those circumstances, the SPM concentrations, and in particular the turbidity, can be (temporarily) increased with respect to the natural background conditions. In addition to antropogenic inputs of SPM, transport pathways of SPM in the coastal system may change when coastline contours are modified due to large-scale land reclamation such as the extension of the Maasvlakte at the port of Rotterdam. Such alterations may affect the circulation and hence SPM transport patterns in the Dutch coastal waters on a wider scale and long term.

For coastal managers the impact of changes in the concentrations or fluxes of SPM on the marine ecosystem is of interest. SPM is determining the turbidity of the water that, in the Dutch coastal zone, controls phytoplankton growth and visibility of prey for certain birds. Secondary possible effects of changes in SPM on the ecosystem are related to the efficiency of food intake by certain juvenile fish and mollusks. For further information on the environmental impacts of changes in SPM in the Dutch coastal zone, in particular related to the construction of the Maasvlakte-2 land reclamation, we refer to Berkenbosch *et al.* 2007, and references therein.

1.3 Monitoring and impact assessment

Authorities responsible for the quality of the coastal waters require that parties interfering with the coastal system monitor and evaluate the environmental impact of their activities to assess whether these comply with permits and (inter)national regulations.

In order to assess impacts of human activities on the SPM conditions in the coastal zone, extensive *in situ* monitoring is the usual approach. Before activities commence, monitoring is applied to help defining the baseline conditions. During activities, monitoring should provide as accurate as possible information on the possible effects. This monitoring traditionally is carried out by means of ship surveys and/or the deployment of moorings equipped with sensors.
Monitoring should enable stakeholders to assess whether activities comply with criteria defined in permits. In the context of the Maasvlakte extension, these criteria are partly formulated in terms of relative changes of SPM concentrations and/or fluxes of the order of 10% (see *e.g.* Van Prooijen *et al.*, 2006, Desmit *et al.*, 2007). Most often, criteria are not even formulated in terms of SPM, but in terms of effects at higher levels in the marine ecosystem (e.g. preservation of certain species). In any case, the monitoring should enable quantitative statements on relatively small changes in a highly variable and dynamic coastal system of which the scientific insights are limited.
A precursor study ('Baseline silt PMR') by WL | Delft Hydraulics in 2006 (Blaas and Villars 2006) indicated that only by means of a combination of data sources a monitoring strategy with sufficient distinctive power can be achieved. In particular, it has been recommended to combine *in situ* observations with remote sensing and transport models. In this way area coverage, temporal resolution, and minimal information redundancy can be obtained.

Apart from impact assessment, monitoring of coastal waters is carried out by authorities in relation to national and international regulations. For example, the European Marine Strategy and agreements such as the OSPAR Convention provide the framework for regular monitoring of the water quality in the coastal zone by the Dutch Rijkswaterstaat. In this context, the study *ToRSMoN* (Roberti & Zeeberg, 2007) has been carried out. *ToRSMoN* has been another NIVR User Support project that focused on the application of satellite-borne remote sensing data of SPM and Chlorophyll of the North Sea for regular monitoring purposes. The conclusions of that study are that satellite monitoring provides a highly valuable addition to the traditional *in situ* monitoring. It provides data (near) real-time, synoptic (instantaneously covering an extensive area) and at low cost. These data are applicable both for short-term purposes (e.g., harmful algal blooms, see also Van der Woerd et al., 2005 and Van der Woerd et al., *submitted*) and also for longer-term interests such as trans-boundary transports and the generation of atlases and online remotely sensed water quality data products (e.g., Pasterkamp et al. 2002, 2003, Peters et al. 2005, Eleveld et al. 2007.)

Within TnulTSM, the results of Baseline Silt PMR and ToRSMoN have been taken to a further stage. Not only satellite remote sensing data are applied to support environmental impact monitoring but, moreover, these data are integrated with numerical transport models to overcome some of the limitations of satellite remote sensing and add additional information to the monitoring and evaluation.

1.4 Objective: instruments for model-supported monitoring

The Port of Rotterdam (PoR) is involved with *TnulTSM* because they are interested in achieving an accurate and cost-effective means to monitor the Dutch coastal water quality in relation to the possible impacts of the extensive sand mining. This sand mining is required for the construction of the Maasvlakte-2 extension (2008-2013). PoR wishes to assess with as much certainty as feasible whether changes in SPM and underwater-light conditions do or do not occur (including effects on algal growth and higher organisms). The relevant scales range from several kilometers to about one hundred and from multiple days to years. Ideally, PoR would like to be able to obtain additional insight in the system to identify causes of any possible change observed.

TnulTSM aims to

- Apply and refine existing techniques of data assimilation in a combination of SPM modeling, remote sensing and *in situ* observations.
- Investigate the technical and economic feasibility of implementation of the techniques in an operational system

The application will eventually provide parties such as PoR (but not exclusively) with monitoring instruments that address their specific needs. Ultimately, these instruments yield more extensive and accurate information on concentrations and fluxes of SPM than can be achieved by means of the individual sources of information separately. This data-model integration could be referred to as model-supported monitoring.

1.5 Report outline

The following chapters summarise the approach and main results of the project, the economic costs and benefits and conclusions and recommendations. In addition, the appendix contains the manuscript of the scientific paper that addresses some of the research and technical questions that rose during the project. The manuscript gives more detailed information on the approach, results and challenges for those interested.

1.6 Acknowledgments

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Last but not least, the constructive contribution of the members of the TnulTSM advisory board to the numerous discussions during the project and review of this report are highly appreciated. In particular, the input and advice of Wil Borst (Blue Pelican /Netherlands Dredging Consultants, Delft) and Onno van Tongeren (Data Analyse Ecologie, Arnhem), both on behalf of the Port of Rotterdam are gratefully acknowledged.

2 Approach

2.1 Introduction

Within TnulTSM, integration of remote sensing and numerical modelling is achieved via a formal data-assimilation technique, Ensemble Kalman Filtering. Figure 2 shows the scheme that has been followed in order to derive the necessary data, prepare the assimilation, and evaluate the results. The three columns define the sources of information applied within the project, the rows identify respectively: externally provided data (green), models and methods to derive data and information (yellow) from these data, and eventual data of interest (pink). In situ data have been reserved for validation and have not been integrated in the assimilation, although technically this would have been feasible.

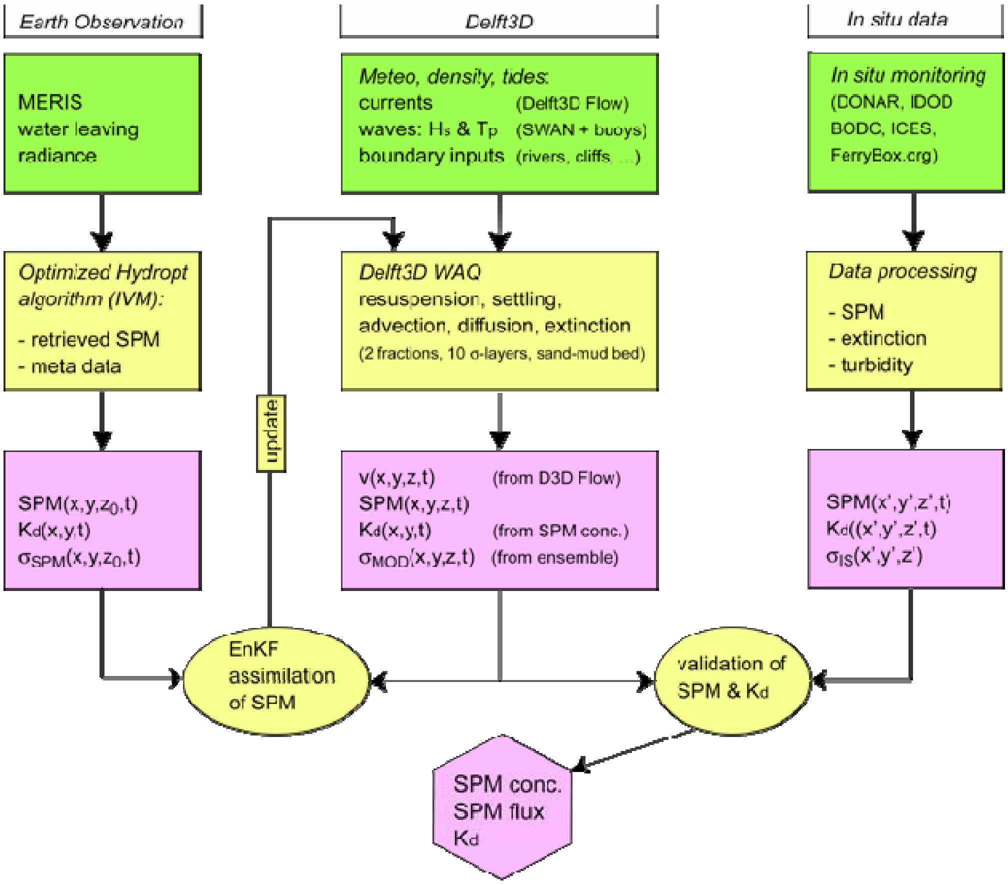

Figure 2.1 Schematic of the information and data flows and the integration of observational data and models within the TnulTSM project.

The sections below further detail the various steps which also correspond to the work packages of the project.

2.2 Remote sensing

Remote-sensing-based SPM data are at the core of the project. In principle, SPM data products from any sensor could have been applied, but for the purposes of the project (demonstration of feasibility) it was decided to apply SPM data retrieved from MERIS for the year 2003. For MERIS, the Hydropt model was readily applicable and 2003 is one of the first years of stable MERIS products. It was decided to postpone the application of MODIS data to a later stage.

Within the remote sensing work package, not only MERIS Reduced Resolution (RR, nominal resolution 1 km) SPM data have been produced, but also an extensive set of meta data and error products. Moreover the applicability of MERIS Full Resolution (FR, nominal resolution 300 m) data has been explored for which we refer to the paper manuscript in the appendix.

Remote sensing (earth observation) data from ESA's MERIS sensor (MER-RR_MEGS7.4 data) were processed using the Hydropt algorithm (Van der Woerd and Pasterkamp, 2008). Hydropt yields Chlorophyll-a, SPM and coloured dissolved organic matter (CDOM) in combination with values for the extinction coefficient (Kd).
Hydropt has been developed over the past years by VU-IVM and uses a forward radiative transfer model parameterized with an Inherent Optical Property (IOP) model that captures the variability in absorption and scattering properties of sea water over the entire North Sea. It relies on physics combined with inverse modelling and hence is different from other methods that rely on regression only. The inverse model has been calibrated with an optimized Specific Inherent Optical Property (SIOP) set, using annual mean in situ concentrations of SPM, Chlorophyll-a and CDOM as collected by Rijkswaterstaat in the regular MWTL surveys. This gives more weight to IOPs specific for the Dutch waters, and it compensates for errors in SIOPs and in atmospheric correction. Figure 2.2 illustrates the application of Hydropt schematically.

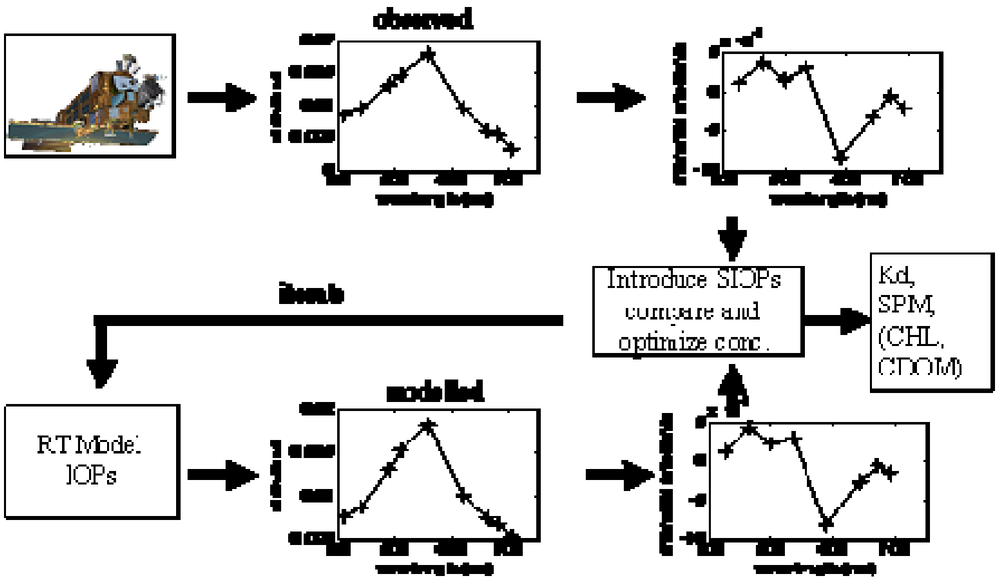

Figure 2.2 Scheme of retrieval of water quality parameters from observed reflectance spectra by the Hydropt model

2.3 Transport modelling

For the modeling, a suite of numerical models has been applied. These comprises the Delft3D FLOW hydrodynamic model (Lesser et al, 2004), the surface wave model SWAN (Booij et al., 1999) and the sediment transport model Delft3D-WAQ (e.g., Van Kessel et al, 2007). These models are applied on a domain covering the southern North Sea (see Figure 2.3). 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 ~ 2x2 km). The grid is coarser in the outer parts of the area included in the model (down to ~ 20x20 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.

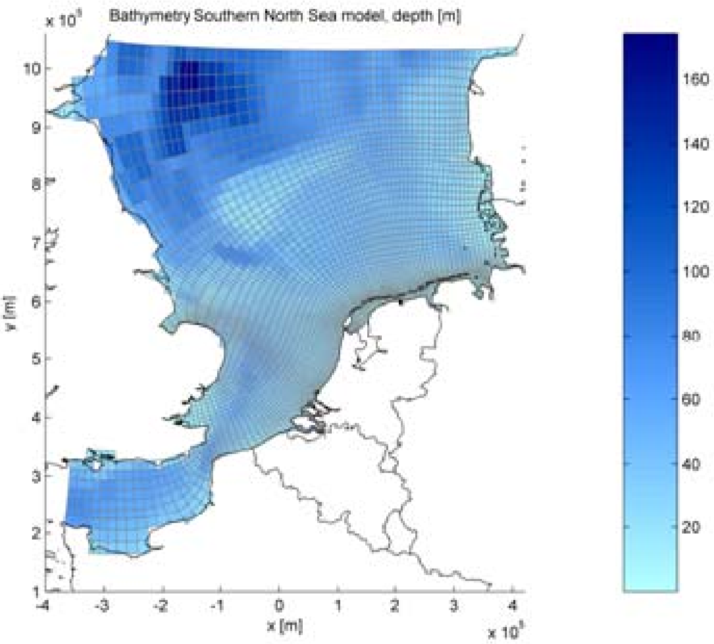

Figure 2.3. Horizontal grid of the Southern North Sea model applications, together with the bathymetry. The individual hydrodynamic, wave and transport models applied all operate on the same grid.

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. The hydrodynamics are governed by tides, wind and density effects and are computed by the Delft3D FLOW model.

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, appropriate wave height and period data are required. 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 (Bram van Prooijen, Svasek BV) with the aid of the spatial patterns in wave parameters derived from a SWAN wave model simulation for 2003.. Like for the remote sensing, 2003 has been chosen as test case because a lot of the required model forcing data were already available for that year. For further details on the model experiments, we refer to the paper manuscript in the appendix.

2.4 Assimilation

Data assimilation exploits the fact that both observations and models depict a certain image of the underlying truth of the system. By means of formal methods, data assimilation aims to arrive at an estimate of the true state that is closer to reality than an individual source of information is able to.

The hydrodynamic and transport models contain several sources of uncertainty. The governing equations may contain inaccuracies due to limited knowledge of the physical processes and their interactions. Also, simplifications must be made to avoid high computation costs. Uncertainties can also occur due to incorrect or incomplete input data of the model, such as initial and boundary conditions, meteorological data, wave data and bathymetry.

To reduce the uncertainties in the model output, data assimilation techniques such as Kalman filter techniques can be applied. Those techniques combine the model forecast with measurement data, using the information on the uncertainties in the model and the measurements to give an improved estimate of the state of the system. In fact, the model is guided by observational information that is becoming available during the simulation. A well-known area of application of data assimilation is the numerical weather prediction, but there are many more fields of application and various methods are available in the literature.

In the field of biogeochemistry, water quality and sediment transport modeling the application is still relatively new. Developments started in the 1990s in mostly academic context currently reach a state where applicability and feasibility for coastal water quality in operational sense become relevant. (See e.g., Robinson and Lermusiaux, 2002, and references therein). For the North Sea, integration of sediment transport model and remote sensing has been explored in the late 1990s by WL | Delft Hydraulics following the variational data assimilation approach (see Vos et al. 2000, Gerritsen et al, 2000). This method requires the construction of a so-called adjoint model that describes the sensitivity of the model results to various uncertain parameters. A drawback of the variational approach is the fact that an adjoint model needs to be constructed which is a laborious and technically challenging task.

For the current project, the choice has been to apply the Ensemble Kalman Filter (EnKF) technique. The advantage of the Ensemble Kalman Filter is the feasibility of relatively fast implementation in complex and highly non-linear models. Within TnulTSM, EnKF is applied to assimilate SPM Remote Sensing data in Delft3D-WAQ sediment transport model, where the uncertainties in both the model and observations are used to sequentially update the model. The sequential updating is illustrated in Figure 2.4 below. The essence of the Kalman Filter is that it provides the weights required to construct the updated solution (analysis state) that serves as input for the next forecast. In a discrete model with discrete observations these weights are present in the so-called Kalman gain matrix in which the uncertainty in observations and the evolved uncertainty in the model state are combined. These uncertainties are represented by covariance matrices. In order to have knowledge of the propagation of uncertainty in the model an ensemble of model runs with perturbed initial conditions has been analysed.

The full EnKF formulation is described by Evensen (2003). El Serafy et al., (2006) discuss a suite of ensemble-type of data assimilation tools recently developed by Deltares and a particular application of Steady State Kalman Filters derived from Ensemble Kalman Filtering for in situ observations of salinity and numerical modeling with Delft3D FLOW. The reader is referred to the manuscript of the scientific paper in the appendix for further information on the method applied within TnuITSM.

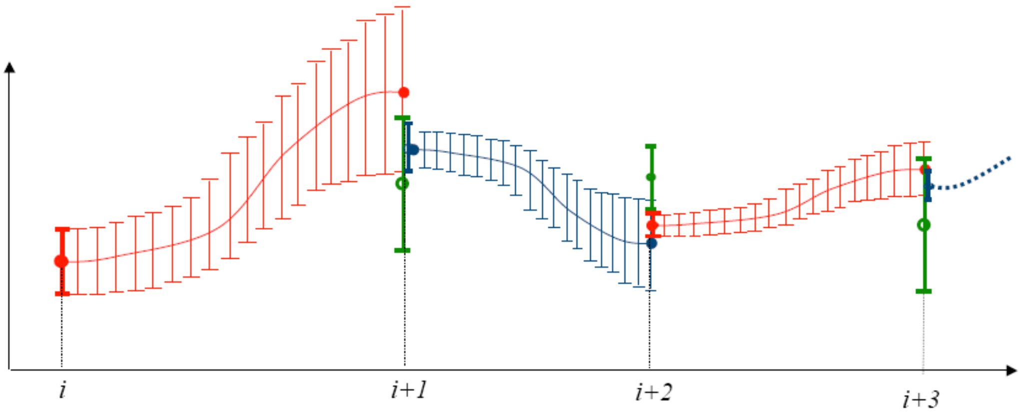

Figure 2.4 Illustration of sequential updating of a fictitious model solution by a general Kalman Filter. Discrete time is progressing on the horizontal axis. Starting points of each forecast are the uncertain initial states (analysis) of the model. Green markers indicate the uncertain observations. Note the deceasing uncertainty in the forcast after several updates. (Graph adopted from Lecture notes of the ESA Summer School, Frascati August 2006, by Pierre Brasseur, LEGI France).

The assimilated model run starts in January 2003 and updates are carried out whenever new remote sensing data are available which for the model domain is in general once or twice a day provided that the swath of the sensor is not obscured by clouds. It should be remarked that in the initial stage the unassimilated startup conditions and adjustment of the sea bed still play a role in the solution. This gradually becomes less during the simulation.

2.5 Verification

In order to evaluate the effect of the assimilation, a comparison has been carried out between the assimilated model results on one hand and the unassimilated (deterministic) model results and the MERIS data on the other hand. This so-called verification demonstrates if systematic differences occur between the three sources of information and what their nature is. It is instructive to gain insight in these differences for future refinements of the techniques. For the verification, animations of spatial maps and maps of measures for Goodness of Fit have been constructed.

2.6 Validation and skill assessment

Validation refers to formal assessment of the quality of the results of the deterministic and assimilated models and the MERIS data against a third, independent information source. Within TnuITSM, validation has been carried out using the in situ observational data of the Belgian, Dutch, and German monitoring of surface SPM concentrations. The Belgian data have been obtained through the IDOD data base of MUMM (http://www.mumm.ac.be/datacentre). The Dutch in situ data originate from the national monitoring program (MWTL) of Rijkswaterstaat and are available via the DONAR database (www.waterbase.nl). The German data have been obtained through the German DOD data base of the BSH (http://www.bsh.de/en/Marine_data/Observations/DOD_Data_Centre/index.jsp)

The available stations with in situ data in the area of interest are shown below in figure 4. This encompasses 67 stations of which 42 have eventually been applied. All stations within the Wadden Sea and Eastern and Western Scheldt have been rejected because both the transport model and the hydro-optical model are not applicable there. The validation partly consists of inspection of time series of the results and partly of determination of quantitative measures for Goodness of Fit.

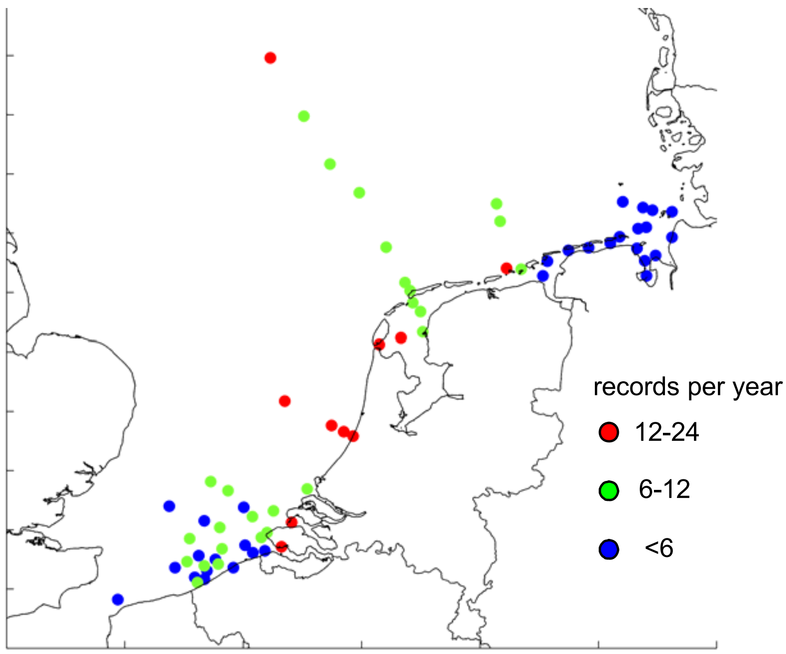

Figure 4 *Location and sampling frequency of in situ stations with SPM observations in 2003. The stations in the Dutch and German Wadden Sea and the Eastern and Western Scheldt have not been applied in the eventual evaluation because both the numerical model and the hydro-optical model have not be designed for those areas where the sediment has distinctly different characteristics.*

3 Results

3.1 Introduction

In the sections below the major results of the relevant work packages as introduced in the previous chapter are discussed. More detailed information can be found in the paper manuscript in Appendix A.

3.2 Remote sensing

The remote sensing data and their value-added water-quality products had to provide the essential parameters for the data assimilation. A novel aspect wit respect to traditional data deliveries is that not only the data of SPM but also extensive information on the uncertainty was produced. This uncertainty information is used to in essence determine the weight of the remote sensing data with respect to the model information in the Kalman Filter. Sources of uncertainty lie in the observation of the spectrum of reflectance by MERIS (noise, atmospheric correction, contamination of the signal by clouds, land, sun glint etc) and in the subsequent retrieval of SPM from the spectrum through HYDROPT. For the assimilation the overall uncertainty matters, but for research purposes it was judged fruitful to have access to the individual components building this error product as well.

The product by IVM consisted of SPM concentrations together with the error products that contain both the MERIS and HYDROPT uncertainties. These are:

- ESA L2 product confidence flags
- σSPM (error in SPM concentration)
- $\chi 2$ and P (confidence measures of Hydropt result)

Also, an estimation of optical extinction coefficient was produced. This variable can be used to determine optical depth and can be related to the depth over which the observed SPM are representative: the clearer the water, the deeper the surface layer over which the sensor is receiving a signal. Finally, metadata consisting of the date and time stamps, lat-lon grids and parameter settings have been delivered.

Figure 3.1 below shows the instantaneous data of Chlorophyll-a, SPM and CDOM (coloured dissolved organic matter) and the associated error products for April 16, 2003 as an illustration. It can be seen that optical depth is mostly controlled by SPM in this case. Besides it is suggested that the error products are more closely correlated than the individual variables. Chlorophyll-a shows a bloom off the southern Delta Islands whereas SPM is maximum in a more elongated coastal strip. CDOM is dispersed more widely than SPM because it is not settling and closely correlated to the dispersion of fresh water.

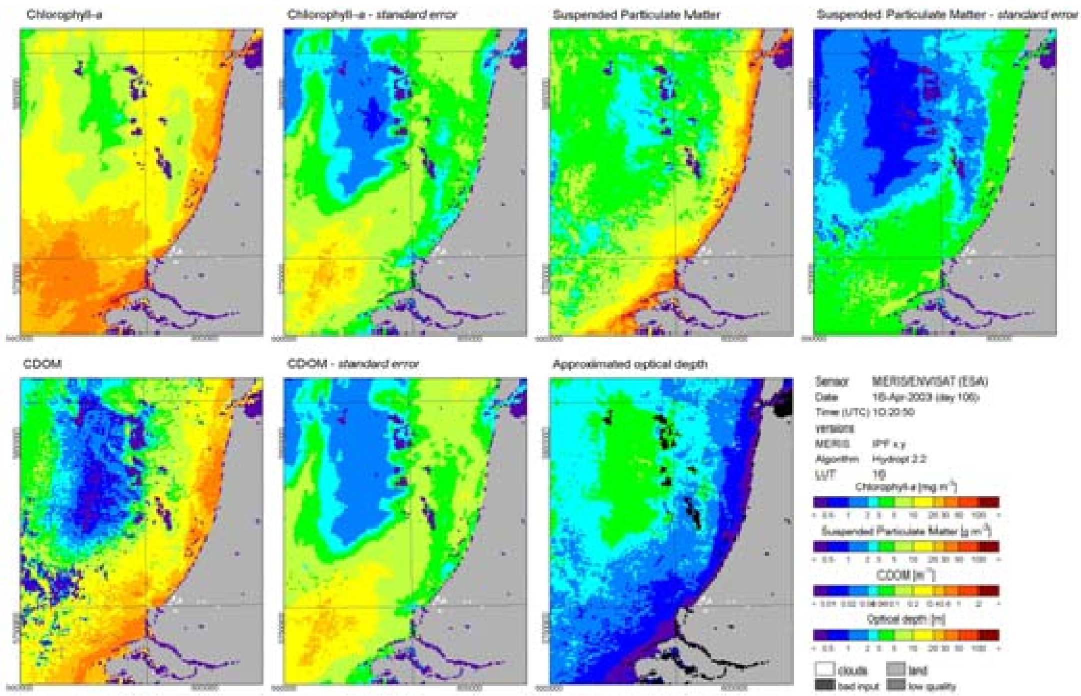

Figure 3.1 Suite of MERIS Reduced Resolution water quality parameters and error products as produced by VU-IVM from the HYDROPT algorithm.

It is concluded that the retrieval by Hydropt, originally developed for Chlorophyll-a for the entire North Sea, also performs well for SPM in the Dutch coast region. The remote sensing SPM retrieval algorithm also provides an indication of the layer from which a signal can still be received and provides error products. The study of Full Resolution data showed that Hydropt performs also well for nearshore use.

3.3 Results of assimilation: feasibility and verification

After construction of the Kalman Filter from the uncertainty information (covariance matrices) of the model and remote sensing data, the assimilation could be carried out.

From a technical point of view it is remarked that the EnKF procedure has been successfully implemented in Delft3D WAQ. Eventually, numerically stable runs could be carried out. Because the computations turned out to be demanding on computer resources, runs had been set up in batches. The handling of the data and updating has been implemented in Fortran scripts. For future applications these scripts may be transferred to a more generic environment.

Inspection of the results properly demonstrated that the solution was not only stable but also physically sensible on most locations and times. The assimilated model turned out to be able to forecast the upcoming (next day) observations quite well, indicating stability of the solution according to the system properties. Nevertheless In periods of data scarcity (prolonged cloudy conditions) the solution is observed to move to the deterministic solution on a timescale of a few days, depending on the prior updates and hydrodynamic conditions.

For the current project, focus has been on the surface concentration values because verification and validation information on the vertical distribution is very limited. The verification assesses the relation between deterministic model, assimilated model and remote sensing data. For this purpose, the comparison is made between the model output and the remote sensing data mapped onto the model grid. The temporal and spatial evolution of the solutions is evaluated, partly by means of animations [which are supplied as a digital appendix to this report] and time series at specific sites.

An example of a time series showing the deterministic, assimilated model results together with the MERIS observations is shown in Figure 3.2 for the station 70 km offshore of Walcheren, in the southwest of the Netherlands.

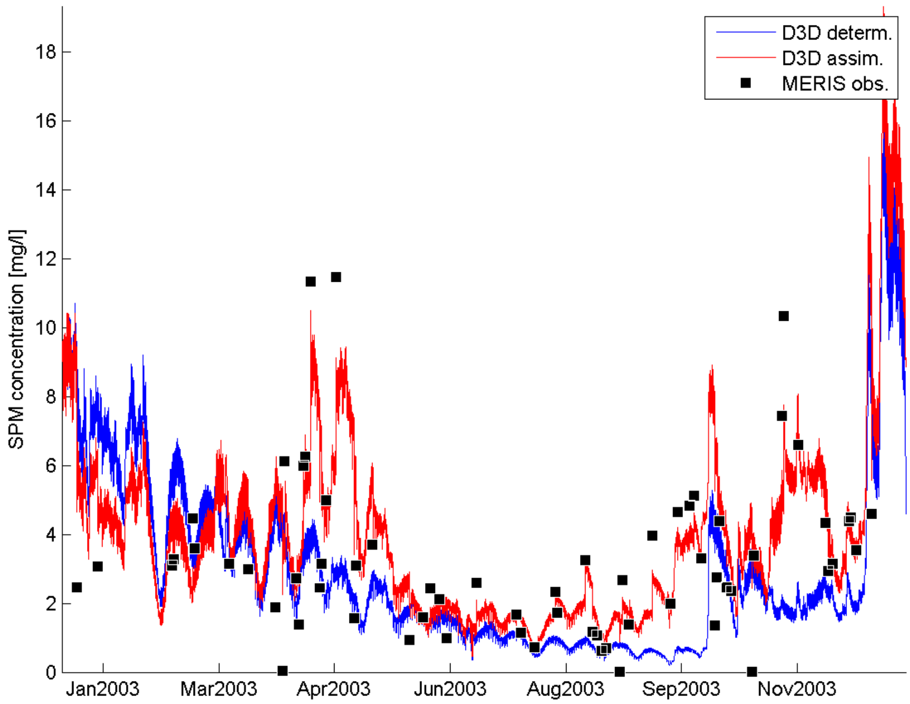

Figure 3.2 Time series of sea-surface SPM concentration from both the deterministic and assimilated model runs (blue and red, respectively) and the gridded MERIS data (black).

From figure 3.2 it can be seen that in the first week of the simulation both runs behave almost identical until local remote sensing data become available. It is also clear that low values in January and February steer the solution towards lower values, whereas in March and April higher values introduce higher excursions. The assimilated model results do not pass through all observations, since a blend of local and non-local effects due to advection is taken into account and both the model dynamics and observations are weighing in.

A condensed picture of the comparison is achieved by means of application of measures that quantify the fit or misfit. Allen et al. (2007) discuss the application of various measures to suspended sediment and biogeochemical models of the North Sea. Stow et al. (2008) apply similar concepts to US models. For the present purpose, we limit ourselves to the following three measures:

RMS difference

$$E = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(M_n - O_n)^2}$$

Bias $$\bar{E} = \frac{1}{N}\sum_{n=1}^{N} M_n - \frac{1}{N}\sum_{n=1}^{N} O_n = \bar{M} - \bar{O}$$

Unbiased RMS difference $$E' = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left((M_n - \bar{M}) - (O_n - \bar{O})\right)^2}$$

Where M_n indicates discrete model data. On observational data; n is time and/or space index depending on whether only temporal or also spatial averaging is considered. N is the number of successful MERIS observations on the model grid in a given time interval. In general, this number is lower than the total number of model data because of cloud cover, flagging and retrieval limitations. The bar is shorthand for averaging. Because both model and observation data are log-normally distributed, differences are assessed after log transformation.

Each measure highlights specific aspects of the differences and correspondence between the data sets. The RMS difference is a convenient measure to illustrate overall differences between data sets that are as variable as the SPM data. It is similar to the mean absolute error (MAE, not shown) but penalizes the extreme outliers. The RMS error contains both a bias component and a component due to the mismatch of variability, represented by the unbiased RMS difference. This is illustrated by the following relation:

$$E^2 = \bar{E}^2 + E'^2$$

Below, we also discuss the bias and unbiased RMS separately.

It is remarked that all data points have received equal weight in the averaging. As an extension one could apply weights proportional to the relative surface area or volume of computational grid segments and inversely proportional to the measurement or model uncertainty at a given time and location.

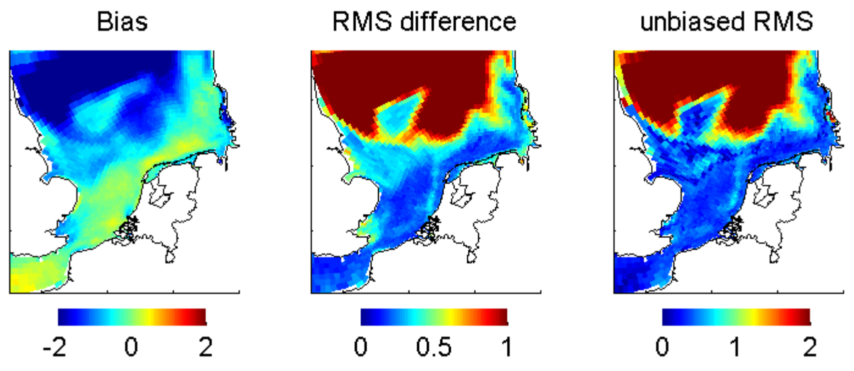

Figure 3.3a Differences [^{10}log(mg/l)] between deterministic model results and gridded MERIS data of SPM on annual time scale for 2003.

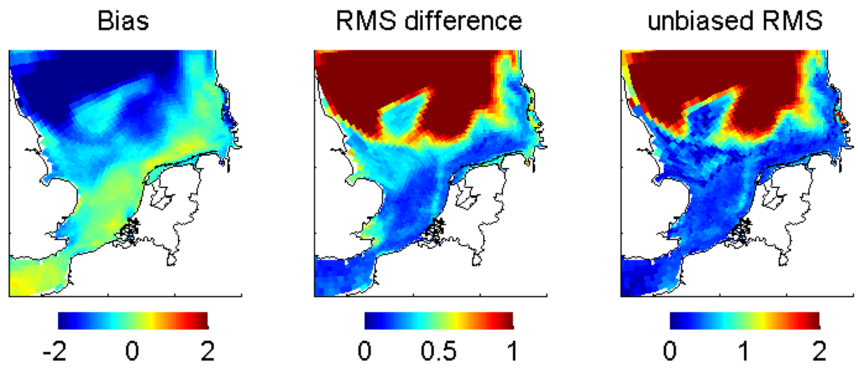

Figure 3.3b As Figure 3.2a, but for assimilated model results and gridded MERIS data.

Figure 3.3a and b show the differences between model and data on annual mean basis for the deterministic and assimilated model respectively. From the overall RMS difference (center panels) it is clear that the misfit has generally decreased. The negative bias of the deterministic model (left panels) in the northern part of the domain has been removed. In the southern bight a slight increase of positive bias can be observed off the coast of North Holland and Texel.
The unbiased RMS difference (right panels) again show the strongest relative improvement in the northern part of the domain, but also both the UIK and Dutch coast in the Southern Bight have clearly improved. Here, the match of temporal fluctuations at each grid location between model and observations has become better.

The results of Figure 3.2 refer to annual averages. Further insight is gained by inspecting seasonal dependence of these misfit measures (not shown). The strong negative bias of the deterministic model is mostly due to the underestimation of suspended matter in the summer season (May-August) when the northern North Sea is thermally stratified. The question rises what SPM fraction is observed by the remote sensing in that area in that season. It is hypothesized that it concerns mostly very small particles, presumably of organic origin (algal detritus) for which the model has not been designed to describe. Here, the application of data assimilation clearly affects the surface concentration values, although it should be kept in mind that also the HYDROPT parameters have not been set to represent the optical properties of the central North Sea water masses (which are more like less turbid Case 1 waters). Moreover, there is little flux of suspended matter from the central North Sea to the Dutch coastal waters which are of primary interest. Therefore, we focus on the coastal areas in the following.

In the Dutch coastal zone, the absolute model bias after assimilation in the first nine months is less than the deterministic model, but in the period September-December gradually increases. This increase appears to be related to the fact that vertical mixing and resuspension increase in this season. Because of the noted underestimation by the deterministic model in the first nine months, the assimilation has introduced a net input of suspended matter in the coastal areas which is partly redelivered to the surface waters in the last three months of 2003. This tendency provides valuable information for future improvements in both the model and the assimilation procedure.

The unbiased RMS difference on the other hand, is consistently lower over all seasons when comparing the assimilated to the deterministic model. This indicates that the representation of variability is consistently improving due to the assimilation.

3.4 Validation and skill assessment

Further insight in the value of the data assimilation and in issues that require future attention is obtained through systematic investigation of differences between model and remote sensing data on one hand and in situ data on the other hand. These data represent the most independent reference set available, although it should be kept in mind that past optimizations of the hydro-optical and numerical models both have relied on annual mean MWTL monitoring data.

When comparing different data sources, issues of representativity rise. The in situ data have a relatively low sampling frequency and represent a small spatial scale and cover a limited part in the time-space domain. The model output on a grid location represents a spatial average over a segment with hourly time resolution. The MERIS data have been mapped onto the grid and as such are comparable to the model data, although they originate from a higher resolution data set. Given the observations, one cannot be conclusive on the veracity of the variability on time scales shorter than the sampling interval. The same holds for information on the vertical profiles. Since in situ data resolving the vertical profile for 2003 are lacking, only statements on the surface concentrations are made here.

Besides, it is noted that in situ sampling may be biased for calm weather conditions because of ship survey policy. This is illustrated by Table 3.1 below which lists the average bottom shear stress due to waves and currents from the model when observed on different sampling instances. This shear stress is the main driver for resuspension in the model as soon as it exceeds the threshold for erosion from the sediment layer in the bed. When the total time series of bottom stress is subsampled according to the occurrence of in situ measurements it is 2.5 Pa, whereas subsampling according to MERIS measurement instances yields 2.7 Pa. The overall mean for all times is 3.8 Pa. Subsampling the supercritical shear stress for two threshold values (τ_{crit1} for resuspension form the superficial bed layer and τ_{crit2} for the deeper buffer layer) leads to even larger relative differences in mean stress between in situ and the MERIS sampling.

Hence, there is a bias towards calm conditions in both the MERIS and *in situ* observations, the *in situ* bias being strongest. This implies that validation against these data only provides corroboration of the model skill for relatively calm conditions whereas part of the added value of the model is expected in resolving cloudy and stormy conditions. This remains an issue for future elaboration. For future follow-up developments in the assimilation of SPM it is foreseen to validate also on in situ data of third parties such as the Port of Rotterdam that also cover the vertical and possibly on continuous time series of moorings that cover events.

Table 3.1 *Mean bottom shear stress from the model determined by subsampling according to the in situ and MERIS observation instances. Rightmost two columns refer to supercritical shear stress beyond indicated thresholds of superficial and buffer layer (τ_{crit1}=0.2 Pa, τ_{crit2}=3.7 Pa respectively)*

mean τ [Pa]	*all τ*	$\tau > \tau_{crit1}$	$\tau > \tau_{crit2}$
in situ instances	2.5	2.7	6.8
MERIS instances	2.7	3.0	7.8
all instances	3.8	4.1	9.0

For validation, again inspection of spatio-temporal behaviour has been carried out by means of time series of the 42 in situ stations. Figure 3.4 shows the addition of the in situ data to the time series for the Walcheren station.

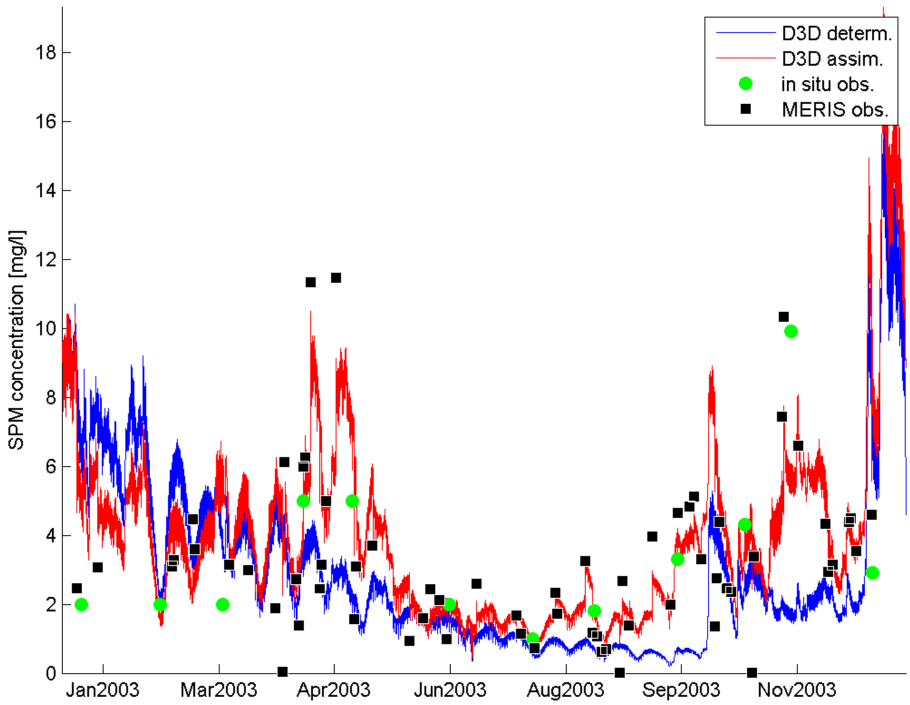

Figure 3.4 *As Figure 3.2 but with the in situ data (green) added.*

At first sight, the model results and MERIS data appear consistent with the in situ observations. For the station Walcheren-70 shown in Figure 3.4 one might conclude that the assimilation has improved the match between model and in situ data. In order to objectively corroborate such statements on model skill, the Goodness of Fit measures introduced in section 3.3 have been determined with respect to the in situ data.

Finally, the question remains over which time and spatial scales can one compare certain MERIS observations to in situ observations. In order to explore the sensitivity of the results to temporal averaging, in the following not only instantaneous data have been compared with each other but also time-averaged data. Moving averages have been applied to all 42 time series. The abovementioned misfit measures have been determined for the instantaneous and moving averaged data.

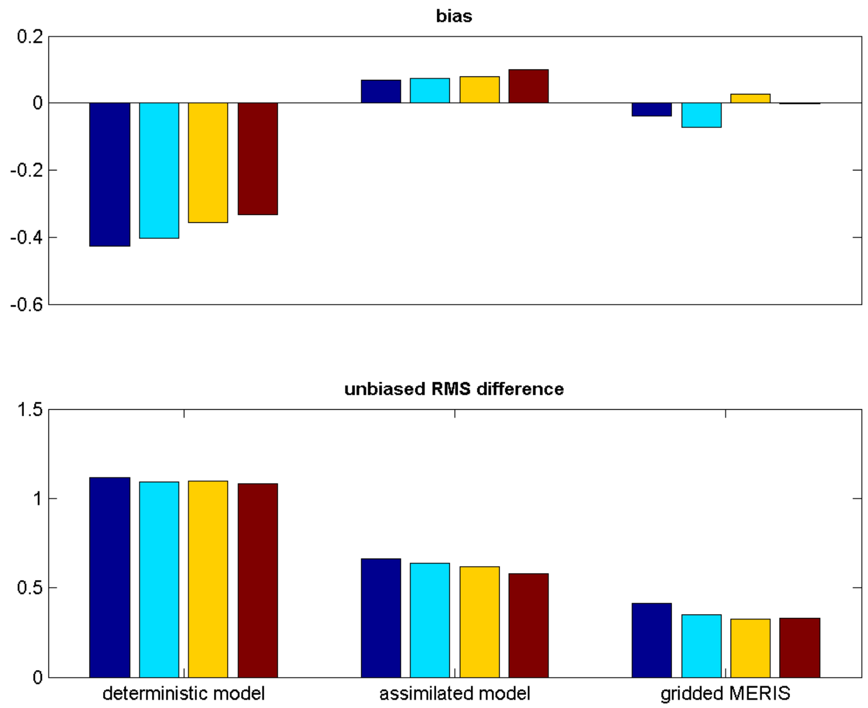

Figure 3.5 Annual bias and unbiased RMS difference for the deterministic, assimilated models and gridded MERIS data all compared to the in situ data of 42 stations. Colors of the bars correspond to instantaneous data (blue), and moving averages of 8 days (cyan), 16 days (yellow) and 30 days (red).

Figure 3.5 shows that gridded MERIS data have smallest RMS difference with respect to in situ data. Hence the decrease of RMS errors for the assimilated results confirms what has been suggested in the verification of section 3.3: Also, the bias is reversed from strongly negative to slightly positive as discussed above. (Because the total RMS difference evolves very similar to the unbiased RMS it has not been shown in Figure 3.5.).

The gain in skill represented by the unbiased RMS difference appears relatively smaller than that represented by the bias. Also the sensitivity for time averaging appears rather limited in most instances. Note however that the MERIS bias is relatively sensitive, but small in absolute sense. After time averaging, the bias of the assimilated model increases, whereas the bias of the deterministic model slightly decreases, *i.e.*, both model results tend towards higher values when averaging over longer timescales. This is consistent with the notion that extending the window of time averaging around the instances of *in situ* observations leads to inclusion of more and higher extremes in line with the fact that in situ surveys are biased for low wave conditions. Because the MERIS data are also, but less strongly biased for fair-weather conditions, the tendency for increasing bias with increasing time window is less obvious (see also Table 3.1 above).

Unbiased RMS decreases for longer time averaging, albeit marginally. It is clearest for the MERIS data. Temporal averaging smoothes part of the variability and hence leads to better capture of the remaining signal fluctuations but, given the in situ sampling frequency of once a month on average, the variability represented in the unbiased RMS is typically of seasonal nature.

3.5 Conclusions

The remote sensing and modelling efforts have resulted in robust components that enabled stable and mostly sensible assimilation of the MERIS data into Delft3D WAQ. Specific issues rise related to applicability of both the optical and transport model in the central North Sea. Nevertheless, these are not expected to directly affect the results on the coastal zone. Within the coastal zone, effects of a long term bias between model and remote sensing are visible, in particular in periods of enhanced vertical mixing after periods of stratification.

After assimilation, the model has gained skill in describing both the annual mean and seasonal variations. The skill is in between that of the deterministic model and the MERIS data. Assessment of skill is however limited to only those instances and scales that are resolved by the validation data. The value of the opportunity to interpolate and extrapolate into unobserved regions in time (e.g., storms) and space (beyond the MWTL grid and over the vertical) can only be assessed by another independent data set that covers these parts of the space-time domain at least locally (e.g. a semi-permanent mooring with high frequency sampling). Future activities are foreseen to elaborate on these aspects.

4 SWOT and Cost Benefit Analysis

4.1 Introduction

In the previous chapters, the technical approach and results of the demonstration project TnulTSM have been presented. The methods for model-supported monitoring developed provide an extension of or partial alternative for conventional *in situ* monitoring by ships and/or buoys of SPM in coastal waters. The main motivation for the application of model-supported monitoring is to obtain a more powerful strategy and more accurate information on the coastal system at acceptable costs. Two typical fields of application have been indicated: relatively short-term and dedicated impact assessment and more longer-term regular monitoring.

This section aims to find an answer to the question: What are the Strengths, Weaknesses, Opportunities and Threats (SWOT) of model-supported monitoring of SPM in comparison to conventional monitoring for obtaining information on SPM? This will be done by means of a SWOT-analysis. This analysis will provide the background against which to evaluate the costs and the benefits of model-supported monitoring. The focus of the analysis will be on the application to impact assessment. For a related discussion on the use and costs of remote sensing data in regular long-term monitoring we refer to the ToRSMoN report by Roberti and Zeeberg (2007). Besides, Van der Woerd et al. (2005, and *submitted*) discuss the benefits of a model-supported early warning system of Harmful Algae in Dutch coastal waters.

The particular goal in this chapter is to obtain insight in the political and economic feasibility for the future development of an SPM data assimilation service for monitoring of effects of the Maasvlakte extension (Maasvlakte-2), as well as benefits of such a service to society in general. For a more general discussion on cost-benefit aspects of earth observation we refer to Bouma et al (submitted).

4.2 Presumptions

Before entering the analysis, reference is made to the intrinsic value of information for the users. This reference relies on the experience of the authors and discussions with stakeholders in the course of the TnulTSM project and on theoretical background information such as provided by Bouma et al (submitted) and Hirshleifer and Riley, (1979) for example. Within the context of TnulTSM, the users of information are either decision makers directly (i.e. coastal managing authorities such a bodies of the Dutch Rijkswaterstaat) or parties (such as the Port of Rotterdam) who are obliged to carry out impact monitoring and who provide information to decision makers and other stakeholders. Other stakeholders may be NGOs who fear adverse effects and exceedance of permitted impact limits.

The value of information in this context lies in the degree to which the information affects the effectiveness of certain judgements and decisions. Judgements relate to questions whether real impacts remain within the limits permitted by authorities. Decisions may for example relate to adjusting the design of an operation or adapting the policy of regulation and judgment. Effectiveness of decisions has an economic aspect: the same information may be obtained at lower costs or additional information may prevent future costs by speeding up procedures or preventing liability lawsuits.

Three perception factors determine the value of information (see also Bouma et al., submitted)

Added value: depends on the confidence decision-makers have in their prior beliefs. The more confident the decision-maker is about his expectation regarding the possible state of a system, or the tighter the decision-makers' probability distribution function, the less likely the decision maker is to invest in (additional) information that may affect his beliefs.

Veracity: depends on the extent to which the decision-maker expects the information to be true. A decision based on an informational message can be false in two ways: the message can lead to incorrectly rejecting the 'true' state (type I error, 'failure to detect problem'), or it can lead to failure to reject the 'false' state (type II error, 'false alarm'). The larger the perceived errors, the lower the value of the information.

Deviation: depends on the content of the information: the more surprising the informational message, or the larger the difference with the existing belief, the greater the likelihood that the prior belief will be updated.

4.3 SWOT analysis

"SWOT" is an acronym that represents Strengths, Weaknesses, Opportunities and Threats. It is a relatively simple tool, often used by organisations for use in strategic planning. By building on strengths, reversing weaknesses, maximising opportunities and overcoming threats related to the product, an organisation can optimise its marketing strategy. Strengths and weaknesses are normally internal considerations; opportunities and threats are considerations with more external influence.

The SWOT analysis has been based on expert knowledge of the TnulTSM team members resulting from years of experience using satellite and model data and other more conventional means. The Strengths and Weaknesses are factors that are related to the technical issues of the data assimilation, whereas the Opportunities and Threats are external factors, for example social aspects of the data assimilation of SPM. For each of the aspects Strengths, Weaknesses, Opportunities and Threats the most important factors related to remote sensing as a source of information in general and the factors relating to TnulTSM specifically, have been listed below.

Strengths

The strengths of the data assimilation are directly related to general strengths of using and combining the different sources of data within the proposed service, i.e. remote sensing (RS), transport model, and *in situ* data:

- RS data can be obtained from regions where no *in situ* data are available. RS is by times the only source of data available;
- Imagery is available at daily frequency; For MERIS alone, each individual North Sea 1 km pixel is on average visited once a week.

- Synoptic (area-covering instantaneous) images are feasible;
- Current level of accuracy of RS data and availability of consistent uncertainty data facilitate assimilation;
- Model application enhances insight in sources and sinks, causes and effects
- *In situ* data provide ground truthing and information on vertical distribution of SPM[1]
- RS data are more cost-effective than *in situ* data with similar information density would be.

The strengths that are specific to the model-supported monitoring in the current context are:

- The development is based on methods and techniques developed in previous research projects;
- The three sources of data complement each other, enabling more accurate estimation of SPM conditions and more powerful distinction of trends. This leads to a better information product than each of the sources alone, particularly because the source with the smallest error weigh in most when updating the predictions

Weaknesses

The general weaknesses of an integrated data-modelling approach, as proposed here, are:

- The RS data dissemination and retrieval infrastructure in Europe is less than optimal. Much effort needs to be undertaken initially (for each satellite sensor) to set up a data retrieval – processing – dissemination chain.
- A limited number of parameters is detectable using RS (chlorophyll, TSM, KD)
- There is spatial and temporal autocorrelation between adjacent measurements which reduces the number of independent data with respect to the apparent information content (Van Tongeren & Van Riel, 2007)
- Cloud cover renders parts of the RS imagery useless
- Deterministic SPM models are sensitive to amplification because of non-linearities
- Validation can be no more conclusive than the accuracy of the available independent data

The weaknesses that are specific to TnuITSM prototype are:

- Distinction organic/inorganic SPM and influence of size fractions is not yet incorporated
- The exchange processes between water column and sea floor in the model are not yet incorporated in the data assimilation
- The model and remote sensing data show systematic differences related to stratification and destratification which need to be resolved
- Currently, all observational information applied in the project comprises the near surface layer
- The validation data applied do not resolve the entire relevant spectrum of scales yet.

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1. The complementary in situ measurements envisioned for the model-supported monitoring are supposed to resolve the entire water column. This is the type of monitoring as proposed by the Port of Rotterdam for the impact assessment of the sand mining for Maasvlakte-2.

Opportunities

General opportunities for a model-supported monitoring service, which incorporates RS data, are:

- RS and numerical models are becoming increasingly accepted as sources of accurate information;
- Availability and use of high spatial and spectral resolution space borne sensors is increasing;
- Development of high frequency *in situ* sensors, ferry boxes, 'smartbuoys' and autonomous sampling vehicles provide improved ground truthing and valuable data streams for assimilation
- Continuous improvements of computer power and information technology enable operational information systems that are affordable and accessible
- Evaluations of monitoring strategies are currently being carried out within Rijkswaterstaat and Deltares (e.g. Laane et al. 2008). Now is the time to demonstrate alternative and more efficient methods of providing the required information (Eleveld & Van der Woerd, 2007);
- New and upcoming legislation (Water Framework Directive, European Marine Strategy, OSPAR, ICES) require integral and trans-national system approach
- International developments such as GMES Marine Core and Downstream Services and increasing public awareness of technical possibilities leads to higher stakeholder expectations and standards on monitoring and information dissemination

The opportunities that are specifically available to model supported monitoring based on TnuITSM are:

- There are possibilities of using the techniques worldwide (because of the generic, physically sound approach);
- There are various large infrastructural projects, dredging and nourishment activities planned or envisioned, nationally (Maasvlakte 2, large-scale beach nourishments in adaptation to climate change (*'Zandmotor', 'zwakke schakels')*, airport and islands off the Holland coast) as well as internationally (massive projects offshore of Dubai, continued activities in South-East Asia);
- Extension of the TnuITSM application:
    - use in hindcast mode to help design monitoring programs for specific regions (improve the efficiency of a monitoring program);
    - use in forecast mode to optimize offshore dredging activities
- The data assimilation techniques developed in TnuITSM (e.g. data assimilation techniques) can be used to develop similar systems for other parameters (e.g. Chlorophyll, extinction)
- And, last but not least, Port of Rotterdam is an interested end-user.

VU-IVM and Deltares express the joint ambition to further develop a system that integrates remote sensing, in situ and model information on variables related to the underwater light conditions. Because of its innovative character this can be a showpiece for the Dutch hydro-engineering

Threats

General threats to the use of a service which incorporates RS data are:

- There is not yet a complete acceptance of RS data and derived information products as a source of accurate information. Some (still) perceive *in situ* data as the “only truth”.
- Public authorities are not always receptive to new technology (internal interests inclined to keep status quo);
- Lack of awareness among potential users of the benefits of the technology;
- Lack of training for interpretation of the value-added information products;

The threats that are specific to model-supported monitoring within TnuITSM are:

- Risk of acceptance. TnuITSM provides a new service which may partially affect conventional, already accepted methods; In situ monitoring will still be essential requirement, but present monitoring programmes may have to be redesigned to optimize the total model-supported monitoring system.
- Continuity of suitable, optical RS data. Currently the data assimilation has been based on the analysis of MERIS images. The MERIS instrument may be decommissioned within about 2 years form now. The transition to another instrument (e.g. MODIS or a MERIS successor) will require some research (calibration and validation) efforts.

4.4 Identified Benefits and Costs

In this section, various benefits of TnuITSM in comparison to the conventional means of in situ measuring will be elaborated. The costs of the model-supported monitoring service evolving from tnuITSM will be detailed and compared to the costs of conventional means of obtaining the similar information. Note that it is impossible to obtain exactly the same information in any other way. The statistical methods that come closest (e.g. Van Tongeren and Van Riel, 2007) are not necessarily mass conservative.

Benefits of TnuITSM

Data assimilation by means of EnKF provides an objective and physically consistent methodology to update the sediment transport model solution with information retrieved from the remote sensing and *in situ* data. The filter exploits the uncertainties present in both the model results and the observations and updates the model solution such that a more accurate representation of the coastal system is obtained, while respecting the model equations (mass balance).

The benefits of TnuITSM lie in the clever combination of remote sensing, models and *in situ* data. SPM maps can be retrieved from remote sensing, but no prediction for SPM conditions can be made from remote sensing data alone. In the case of cloud cover, only a partial map (or even no map at all) can be derived from the remote sensing data. Models, on the other hand, are capable of making predictions for any time of day, at any temporal frequency during the period of study. Also, models can extrapolate in depth and be used to bridge the gaps in time. *In situ* data can provide accurate information of the ground truth, but cannot give forecast information. In situ data, however, offer the possibilities of obtaining additional parameters (e.g. nutrient and salinity concentrations, velocity and turbulence data); vertical profiles and high frequency sampling in case of fixed-site moorings or ferry boxes.

By combining these three sources of data, each with their unique characteristics, and by applying data-model integration techniques, more accurate reconstructions (reanalyses) and predictions can be obtained.

Quantification of these technical benefits into economic terms (utility) depends on the costs of certain measures following from the information. In particular, the costs prevented or reduced by applying more accurate information play a role. Prevented costs are related to efficiency and to reduction of liability risks. Reduced risk of liability on one hand relates to detecting real trends (low probability of type I error) and subseqeuntly being able to identify or exclude certain causes. On the other hand reduction of liability risks is achieved by unequivocally identifying the absence of trends (low probability of false alarms, type II error). Since the information upon liability cases is currently lacking, only increased efficiency is taken into account here. Hence, the estimates below can be considered as conservative.

As indicated in Blaas and Villars (2006), a sufficiently powerful monitoring strategy for the Maasvlakte-2 based on only one of the *in situ* data sources is only achievable by monitoring effort spanning at least several decades. In fact, the traditional *in situ* approach (a network of about 20 low-frequency survey stations or just one or two high frequency moorings) might render the monitoring for sand mining, which takes place for only a limited number of years, virtually useless. Incorporation of model information and/or remote sensing allows to shorten the required monitoring period or reduce the effort otherwise and as a bonus increase insight in causes and effects. Blaas and Van den Boogaard (2006) presented a case where a reduction in monitoring time span or effort by a factor of four was obtained when model information is incorporated into high-frequency observations at one site.

Costs of model-supported monitoring (TnulTSM)

The major sources of costs of the full development of TnulTSM include:

- Set-up costs of models (mainly one-off);
- Image acquisition costs;
- RS Algorithm development (mainly one-off)
- Development of data-assimilation techniques (mainly one-off);
- Processing & analysis of imagery, model and DA results;
- Operationalisation of the DA system (mainly one-off);
- Maintenance of service infrastructure;
- Production and dissemination of end-user information products

The costs will increase with:

- use of multiple data products or data from additional RS or *in situ* instruments or time instances;
- increase in RS or model accuracy requirements;
- duration the system will be run operational (number of information products to be produced).

The costs of setting up and producing the model and RS data (total of the current TnulTSM project and anticipated costs of the follow-up project) are given in a separate section below which is confidential.

Costs of in situ monitoring

The major costs of in situ monitoring are:

- Set-up costs (one-off);
- Personnel;
- Calibration of instruments;
- Monitoring program planning;
- Boat time / laboratory time;
- Processing and analysis of data;

The costs increase with:

- number of survey sites and sampling stations;
- number of parameters per station;
- increase in accuracy requirements;
- combining multiple instruments.

An estimation of the cost is provided in in a separate section below which is confidential and therefore not included in this version.

The conclusion is that one-off investments for model-supported monitoring are about five times higher than ship-based monitoring, but that annual operational costs for model-supported monitoring may be less than half the operational costs of ship-based monitoring. Here it should be noted that a modest ship-based programme has been assumed that nonetheless is assumed to have similar power as the model-supported approach. This is a conservative assumption favoring ship-based monitoring in the present analysis.

Starting from the (default) ship based monitoring in a 5-year programme, one can then conclude that a combination of ship-based monitoring and model-supported monitoring is more cost effective as soon as one can reduce the annual ship costs by a factor of about 2.5. Given the tentative results of Blaas & Van den Boogaard (206), this would be feasible while retaining the same power. It should be kept in mind dat also for a model-supported monitoring porgramme, at least limited ship based monitoring remains an essential element.

5 Conclusions, recommendations, outlook

5.1 Conclusions

The demonstration project TnulTSM aimed to investigate the technical and economic feasibility of the application of Ensemble Kalman Filtering (EnKF) to assimilate MERIS Reduced Resolution SPM data into the Delft3D WAQ sediment transport model. This investigation has been motivated by the needs for more accurate and powerful means of monitoring SPM in the Dutch coastal zone. In particular, the Port of Rotterdam has expressed their needs within the context of Environmental Impact Assessment of the sand mining for the Maasvlakte-2 extension. Port of Rotterdam will adopt the technology developed within TnulTSM in order to set up an operational model-supported monitoring system in the coming years.

It can be concluded that the project has succeeded in showing both technical and economic feasibility. Also, it has contributed to scientific progress and opened opportunities for broader applications.

Technically

- The investments in earth observation and in particular development of the hydro-optical retrieval model Hydropt over the past years pay off as demonstrated from the sufficiently stable quality of the MERIS SPM data obtained within this project. In particular, the availability of consistent meta data and uncertainty information greatly facilitated the data assimilation.

- Also, continuous developments of sediment transport modeling capability have proven their value. The Delft3D transport model has shown to be sufficiently accurate to allow for assimilation of surface concentrations by means of EnKF.

- Finally, the efforts in developing and applying robust and generic data assimilation techniques based on Ensemble Kalman Filtering provide the essential bridge between the two information sources.

Verification of the results demonstrated not only the general quality and consistency of the results but also highlighted specific inconsistencies. In particular, biases between the model and both *in situ* and MERIS observations, the transition from stratified to well mixed conditions and the incorporation of fluxes to and from the sea bed require future attention. Validation against in situ data confirm these notions.
IN conclusion, the assimilated model has gained skill in describing both the annual mean and seasonal variations. The skill is in between that of the unassimilated model and the MERIS data. Assessment of skill is however limited to only those instances and scales that are resolved by the validation data.

Economically

Using ship based monitoringas a reference it is concluded that a combination of ship-based monitoring and model-supported monitoring is more cost effective as soon as application of model-supoprted monitoring allows for a reduction of ship costs by a factor of about 2.5. This is a conservative estimate which only takes into account direct costs related to monitoring and modelling and not any potential savings of prevented lawsuits or gained effciency in sand mining operations. Also it has been assumed that the intrinsic value (in terms of distinctive power) is the same for both monitoring strategies compared. In reality it is however very likely that model supported monitoring will have more power at the same costs.

It should be kept in mind that also for a model-supported monitoring programme, at least limited ship based monitoring remains an essential element.

Scientifically

Science has profited from the innovations achieved within TnuITSm also, as witnessed by the three contributions to the 2007 Eumetsat Conference (Blaas et al, 2007, Eleveld et al, 2007, El Serafy et al, 2007), the paper manuscript submitted to Journal of Geophysical research (El Serafy et al, in prep., appendix A), the accepted contribution to the Ocean Optics Conference 2008 (Eleveld et al, 2008) and another journal paper in prepraration (El Serafy et al, in prep). The papers not only address the technical achievements, but also the additional insight in the sediment transport system (transport processes and optics) that fosters future improvements and broader applications.

5.2 Recommendations

From a scientific and technological point of view it is recommended to take care of the lessons learned from TnuITSm. Further investment in resolving the following issues and extension of the scope are envisioned (listing the most prominent)

- Include another year as development case: For 2007 additional in situ data are available from the Port of Rotterdam (PoR) which will provide coverage of the vertical and different spatial locations.

- Include MODIS and in situ data in assimilation: Hydropt has now been refined to also process NASA's MODIS data. Also, with the PoR data and, possibly, mooring and ferry box data, sufficient in situ data are available so that part of them can be included in the assimilation, whereas the remainder is reserved for validation.

- Improve or modify numerical models: increase spatial resolution, improve representation of Rhine ROFI (Region of Fresh Water Influence), exchange and buffering of SPM at sea floor, further refinement of wave and atmospheric forcing

- Refine the Hydropt model to deal with mixed organic-inorganic fractions and spatio-temporal variations in IOPs.

- Refine existing EnKF algorithm for updating the vertical concentration profiles by further use of remote sensing meta data and system knowledge. Possibly, extend the number of state variables.

- Exploration of EnKF techniques that make operational use faster

- Parameter estimation, such that not only the state variable(s) but also parameters determining system properties such as settling velocity, eddy diffusivity and erosion rates can be optimized.

- Incorporation of point sources related to sand mining activities.

From a economic and applied point of view, further exploration into the costs and benefits of having access to a more powerful monitoring strategy is required. Quantification is hampered by the limited knowledge of concrete maximum levels of acceptance and costing of consequences at higher trophic levels in the ecosystem and not meeting certain obligations. Also a more complete power analysis of various monitoring strategies in the context of Maasvlakte 2 is still underway (e.g. Van Tongeren and Van Riel, 2007

5.3 Outlook

The future developments will be partly focused around the interests of PoR. PoR is aiming for an operational model-supported monitoring system that relies on regular retrieval of SPM (and related parameters such as Kd) from Remote Sensing.
From these data monthly composites can be constructed with and without data assimilation. Building the records of SPM data long-term area covering fields can be evaluated for trends or anomalies. The model will provide not only interpolation and extrapolation into unobserved areas but also additional insight in sources, sinks and causes of certain trends or anomalies. Guided by the continuous remote sensing observations, dedicated *in situ* cruises will be carried out to either track down anomalies, or provide updates for the optical and transport model calibration and validation. If required forecasts can be generated and/or a connection can be made to process-based algal modelling (most straightforwardly using the Generic Ecological Model GEM based on Delft3D WAQ).

Notwithstanding the focus on PoR interest described above, more opportunities are expected. Since the techniques are generic they can be applied in different regions and on somewhat smaller scales as well. For the Dutch Rijkswaterstaat there are opportunities to apply the techniques above in very similar manner as PoR for monitoring of SPM related to mining and deposition of beach nourishment sands.
On a smaller scale, dredging operations may profit from application of model-supported real-time monitoring, in a fashion in line with RESTSCOD (e.g. Tatman et al, 2007).

6 References

Allen, J.I., J.T. Holt, J. Blackford and R. Proctor (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

Berkenbosch R.J., G.J.M Meulenpas, L. Brouwer, M. van Ledden, F. Heinis, C.T.M. Vertegaal, M. van Zanten & H. de Mars, (April 2007), Milieueffectrapport Aanleg Maasvlakte 2, Hoofdrapport. Ref. 9R7008.A1/RO11/MVZ/IBA/Rott1)

Blaas, M., El Serafy, G.Y.H., van Kessel, T., De Boer, G.J, Eleveld, M.A., Van der Woerd H.J., (2007). Data Model Integration of SPM transport in the Dutch coastal zone. Proceedings of the Joint 2007 EUMETSAT / AMS Conference.

Blaas, M. and M.T. Villars, Baseline Silt PMR: Assessing changes in SPM conditions off the Dutch coast related to Maasvlakte-2. Final Report Z4046, WL | Delft Hydraulics, November 2006

Blaas, M., and H.F.C. van den Boogaard, 2006, Statistical methods to assess the impact of MV2 on SPM along the Dutch coast. Report Z4046.30, WL | Delft Hydraulics, November 2006

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

Bouma, J.A., H.J. van der Woerd, O.J. Kuik (submitted) Assessing the value of information for water quality management in the North Sea. Submitted to Journal of Environmental Management.

Desmit, X., J.G. Boon, T. van Kessel, & A.J. Nolte, 2007, Sensitivity analysis sand mining scenarios Maasvlakte 2. WL | Delft Hydraulics Report Z4103.70, March 2007.

Deltares, 2008 Schedule of Requirements PMR Compensation Monitoring Voordelta. Call for proposals on monitoring. Deltares, July 2008, Z4572, 136 pages

Eisma, D., 1981, Supply and deposition of suspended matter in the North Sea, Special Publications of the International Association of Sedimentologists, 5, 415-428.

El Serafy, G.Y., Blaas, M., Eleveld, M.A., Van der Woerd, (2007). Data assimilation of SPM from satellite data in Delft3D-WAQ for the North Sea. Proceedings of the Joint 2007 EUMETSAT / AMS Conference.

El Serafy, G.Y. and H. Gerrtisen, S. Hummel, A. H. Weerts, A. E. Mynett and M. Tanaka (2007) Application of data assimilation in portable operational forecasting systems □ the DATools assimilation environment. Ocean Dynamics 57(4-5), pp. 485-499, September 2007.

Eleveld, M.A., H.J. van der Woerd, G.Y. El Serafy, M. Blaas, T. van Kessel, G.J. de Boer, 2008, Assimilation of Remotely Sensed Observations in a Sediment Transport Model, Ocean Optics XIX, Pascoli, Italy, October 2008.

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. & H.J. van der Woerd, 2007. Patterns and dynamics in chlorophyll and TSM-densities in the southern North Sea. In: J.R. Roberti, J.J. Zeeberg, (eds), Does satellite observation of chlorophyll-a and suspended sediment complement Rijkswaterstaat monitoring of the North Sea? (53515 AGI 'ToRSMoN'). AGI-2007-GPMP-017, pp. 26-28.

Eleveld, M.A., Wagtendonk, A.J., Pasterkamp, R. & de Reus, N. (2007). WATeRS: An open Web Map Service with near-real time MODIS Level-2 standard chlorophyll products of the North Sea. International Journal of Remote Sensing 28 (16): 3693–3699 (doi:10.1080/01431160701253204)

Fettweis, M. & D. van den Eynde, 2003, The mud deposits and the high turbidity in the Belgian-Dutch coastal zone, Southern Bight of the North Sea, Continental Shelf Research, 23 (7) 669-691.

Gerritsen H.G., R.J. Vos, Th. Van der Kaaij, A. Lane, J.G. Boon, (2000) Suspended sediment modelling in a shelf sea (North Sea). Coastal Engineering 41, pp. 317-352.

Hirshleifer, J. J.G. Riley, 1979, The analysis of uncertainty and information – an expository survey. J. Econ. Lit. 17, 1375-1421.

Jones, S.E.,C.F. Jago, A.J. Bale, D. Chapman, R.J.M. Howland, & J. Jackson, 1998, Aggregation and resuspension of suspended particulate matter at a seasonally stratified site in the southern North Sea: physical and biological controls, Continental Shelf Research, 18 (11) 1283-1310.

Laane, R.W.P.M. et al, 2008, Integrated monitoring of the carrying capacity of coastal waters. NWO-ZKO proposal, granted spring 2008. http://www.nwo.nl/nwohome.nsf/pages/NWOA_7D3JCC)

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.

Pasterkamp, R., M.A. Eleveld, H.J. van der Woerd, M. van Drunen, 2003. Noordzeeatlas voor zwevend stof op basis van satellietbeelden in 2001. Report AGIGAR200338, Rijkswaterstaat Adviesdienst Geoinformatie en ICT, Delft, 44 pp.

Pasterkamp, R., Van Drunen, M., Eleveld, M. & Gilbert, A., 2002. Atlas of suspended sediment transport for the North Sea: Based on satellite imagery of 2000. Report RIKZ/IT/2002.102. RIKZ, Den Haag, 34 pp.

Peters, S.W.M., Eleveld, M., Pasterkamp, R., Van der Woerd, H., Devolder, M, Jans, S., Park, Y., Ruddick, K, Block, T., Brockmann, C., Doerffer, R, Krasemann, H., Röttgers, R., Schönfeld, W., Jorgensen, P.V., Tilstone, G., MartinezVicente, V., Moore, G, Sørensen, K., Høkedal, J., Johnsen, T.M, Lømsland, E.R., Aas, E., 2005. Atlas of chlorophyll-a concentration for the North Sea based on MERIS imagery of 2003. Vrije Universiteit Amsterdam, Amsterdam, 121 pp.

Roberti, J.R. & J.J. Zeeberg (eds.), Does satellite observation of chlorophyll-a and suspended sediment complement Rijkswatrstaat monitoring of the North Sea? 53515 AGI ToRSMoN, RWS-AGI Report AGI-2007-GPMP-017, a collaborative effort by Argoss, RWS RIKZ, VU-IVM and NIOZ. June 2007

Robinson, A.R., and P.F.J. Lermusiaux, 2002, Data assimilation for modeling and predicting coupled physical-biological interactions in the sea. The Sea, Vol. 12, A.R. Robinson, J. McCarthy & B.J. Rothschild eds., Wiley NY.

Tatman, S, 2005, Remote sensing benefits water systems. In: *Made in Holland / Land and water international.* - Issue 109 (October 2005) ; p. 14-15, Ministry of Economic Affairs (EVD), The Hague, 2005

Tatman, S, Kleissen, F.M., Boot, G. 2005, REmote Sensing as a Tool for Scheduling and Control Of Dredging phase 2 (RESTSCOD-2) : WP 1.2 - a pre-operational tool for assessment of dredging plumes. WL | Delft Hydraulics Report, 2005 (Dec.) 39,p. (Doelfinanciering V&W / OC&W), co-funding to National User Support Programme (GO-2)/NIVR project 53513 WL (Z3419)

Tatman, S., W. Dirks, H. gerrtisen, H. Noorbergen, G. Hesselmans, 2007 REmote Sensing as aTool for Scheduling and Control Of Dredging - phase 4 (RESTSCOD-3) : embedding phase. WL | Delft Hydraulics report, 2007, 63 p. + CD-ROM Nationaal Programma GO-2 / NIVR

Tatman S., Gerritsen H., Hesselmans G., Dardengo L., Dirks Wl, Noorbergen H., Kleissen F., Boogaard van den, H., 2004. REmote Sensing as a Tool for Scheduling and Control of Dredging (RESTSCOD) Inception Phase. NIVR / USP report (project reference 2.1 DE05).

Stow C.A., J. Jolliff, D.J. McGillicuddy Jr., S.C. Doney, J.I. Allen, M. A.M. Friedrichs, K.A. Rose, P. Wallhead, 2008, Skill assessment for coupled biological/physical models of marine systems, J. Mar. Sys. (in press May 2008).

Van Alphen, J.S.L.J., 1990, A mud balance for Belgium-Dutch coastal waters between 1969 and 1986, Neth, J. Sea Res., 25 (1/2) 19-30.

Van der Woerd, H.J., Blauw, A., Pasterkamp, R., Tatman, S., Laanen, M., Peperzak, L., 2005. Integrated Spatial and spectral Characterisation of Harmful Algal Blooms in Dutch coastal Waters (ISCHA). Demonstration of a HAB service in the Zeeuwse Voordelta, IVM report R 05/09 Amsterdam

Van der Woerd, H.J., Blauw, A., Peperzak, L., Pasterkamp, R. (submitted), A harmful algal bloom warning system for the North Sea: a combination of file data, remote sensing and computer models for algal growth and bloom transport. J. Sea Res. submitted April 2008

Van Kessel, T., J.C. Winterwerp, B. van Prooijen, M. van Ledden, W.G. Borst, 2008, modelling the seasonal dynamics of SPM with a simple algorithm for the buffering of fines in a sandy seabed, Proc. INTERCOH 2007, Brest

Van Prooijen, B., T. van Kessel, A.J. Nolte, F.J. Los, J.G. Boon, W. de Jong, & M. van Ledden, 2006, Impact sand extraction Maasvlakte 2, Mud transport, nutrients and primary production. Royal Haskoning, Svašek Hydraulics, WL | Delft Hydraulics report 9P7008.O9

Van Tongeren, O.F.R., van Riel, M.V., 2007. MEP slib een schets van de gewenste opzet van een meetprogramma. Concept rapport.

Villars. M.T., S. Tatman, L. Verhage and M. Turner, 2002. Data Model Integration and Total Suspended Matter; Analysis of SeaWiFS remote sensing data and DMI methods for assessment of TSM in the North Sea. WL | Delft Hydraulics Research Report. Z3293a. December 2002.

Villars. M.T.. R.J. Vos. (1999). RESTWES; REmote Sensing as a Tool for integrated monitoring of the Western Scheldt. WL | Delft Hydraulics report Z2472; BCRS report 0009. Delft. The Netherlands.

Vos, R.J., P.G.J. ten Brummelhuis & H. Gerritsen, 2000, Integrated data-modelling approach for suspended sediment transport on a regional scale, Coastal Engineering, 41, 177-200.

Winterwerp, J.C., 2006, Fluxes of fine sediment along the Dutch coast and the impact of Maasvlakte 2, A system description, WL | Delft Hydraulics Report, Z4046.10 October, 2006

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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).

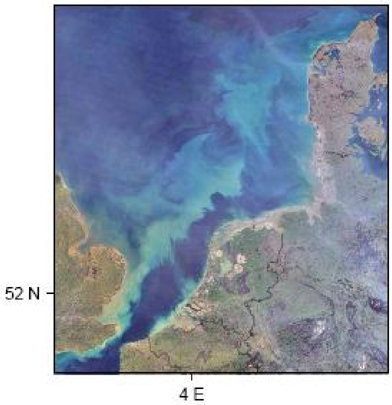

Figure 1 MODIS (Terra) recording of the southern North Sea, March 26, 2007, illustrating spatial distribution of suspended matter in the surface water. (Image courtesy MODIS Rapid Response Project NASA/GSFC

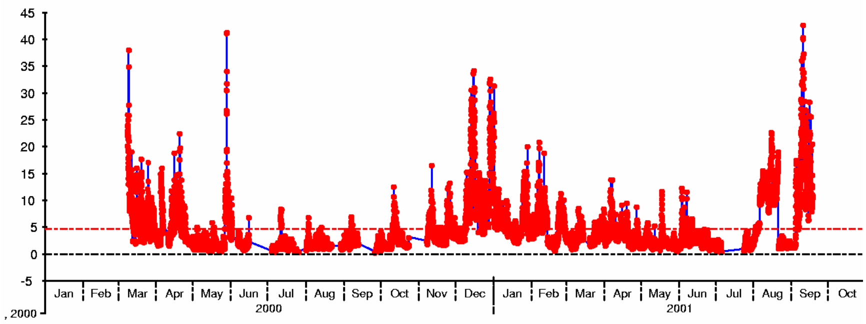

Figure 2. Time series of SPM surface concentration observed by the OBS on the Cefas-Rijkswaterstaat Smartbuoy mooring 10 kilometers off Noordwijk. Dashed red line denotes temporal mean.

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, Fettweiss 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 (Kd_{560}) 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.

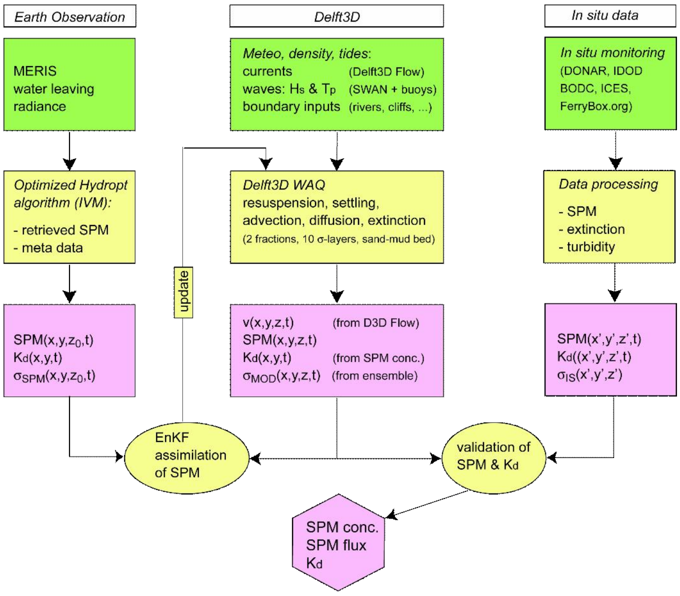

Figure 3. Scheme of the data-model integration applied to obtain improved accuracy data sets of SPM concentrations and associated fluxes and extinction coefficients.

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 $\varsigma = 1/K_{D560}$ 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: $\chi^2_{\rho w}$, 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).

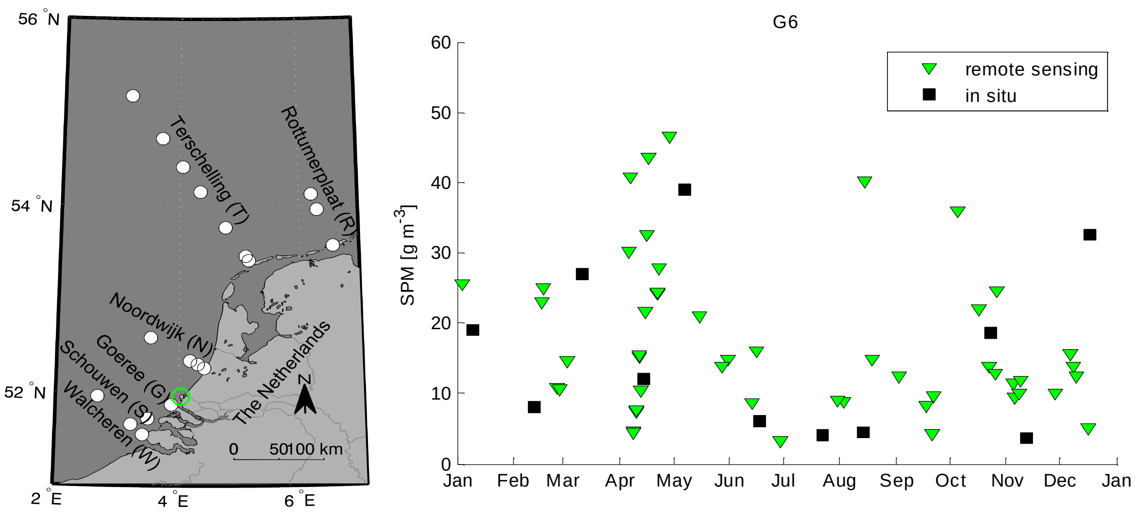

Figure 4 Comparison. The algorithm validates well for nearshore (2 km) and offshore (235 km) stations. Presented are results for station G6, which is located 6 km offshore near the dredging location for the extension of Rotterdam Harbour.

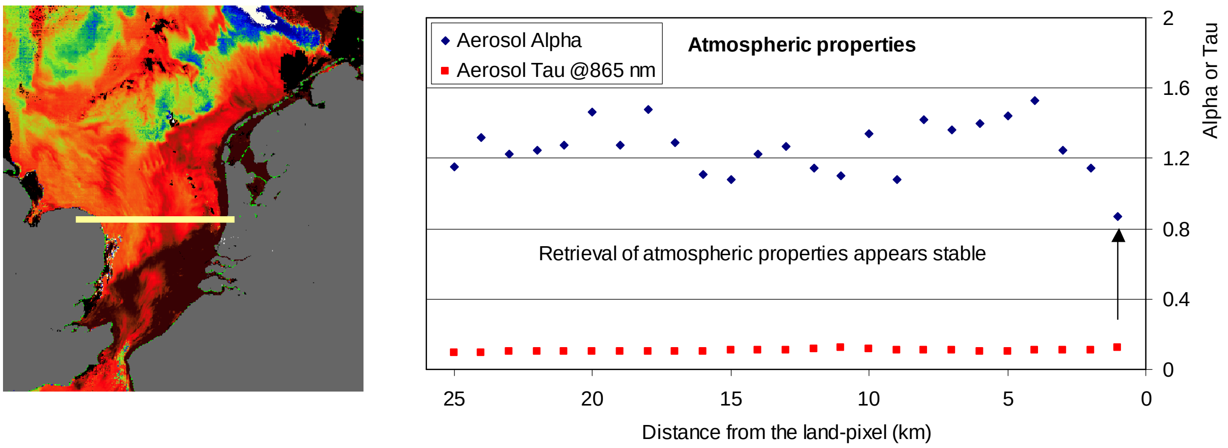

Figure 5 left: Transect on a MERIS Reduced resolution image of 16 April 2003; **right:** Atmospheric properties along the last 25 km of the transect approaching the Dutch coast. The aerosol optical depth at 865 nm varies offshore, but is considerably lower in the first km. Alpha, the baseline to estimate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

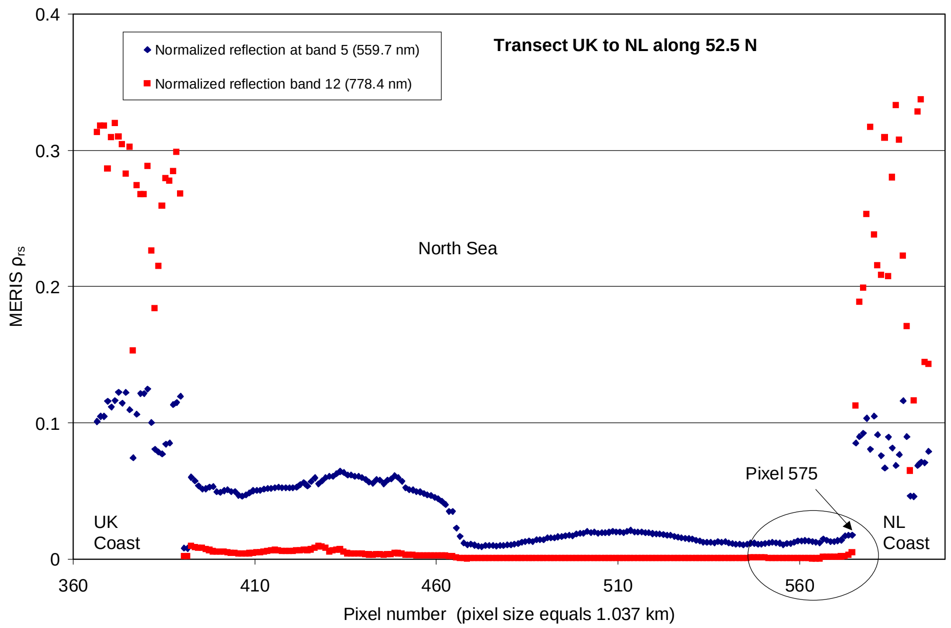

Figure 6 Reflectance along the transect at 560 nm (high SPM signal) and 778 (high water absorption).. Some problems in the atmospheric correction seem to occur in the first pixel classified as sea (pixel 575) in the Reduced Resolution data. For Full Resolution similar problems occur in the first kilometre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

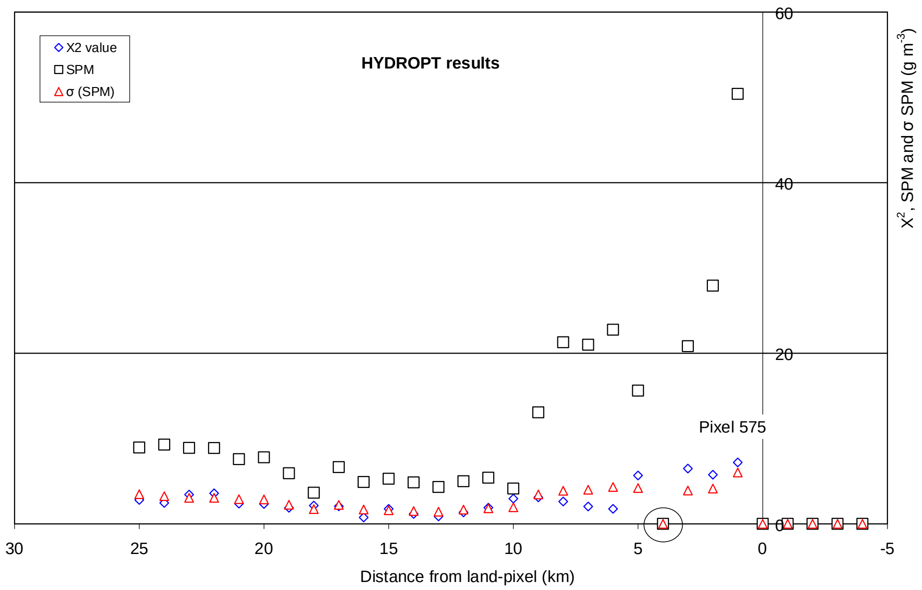

Figure 7 HYDROPT seems to perform robustly in the nearshore zone. Values for X^2 are not increasing much going landward. Minor changes in atmospheric parameters seem to be mitigated by the algorithm. Standard error σ is relatively low for high nearshore SPM concentrations. In some situations the algorithm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

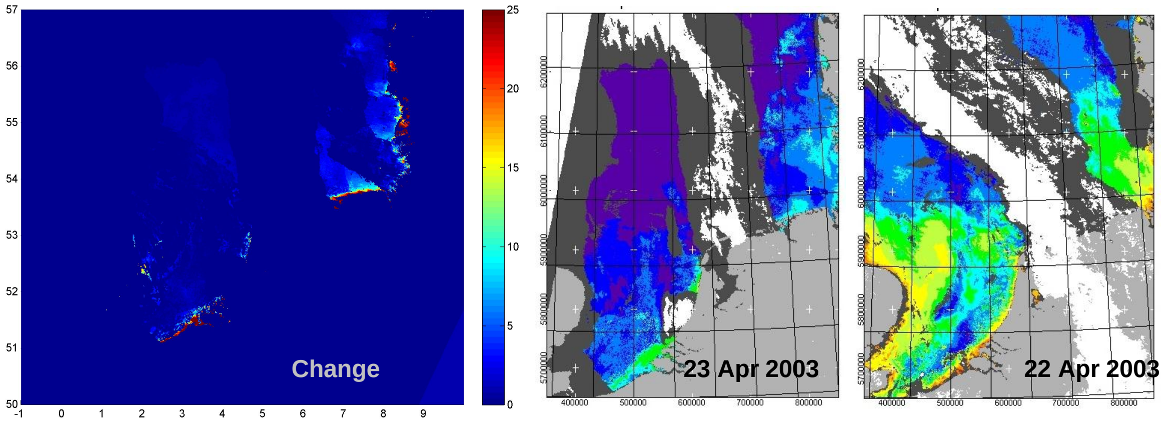

Figure 8 Remote sensing registers change between observations. (See Fig. 9 for legend April data.)

(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 $\leq$ 1m 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.

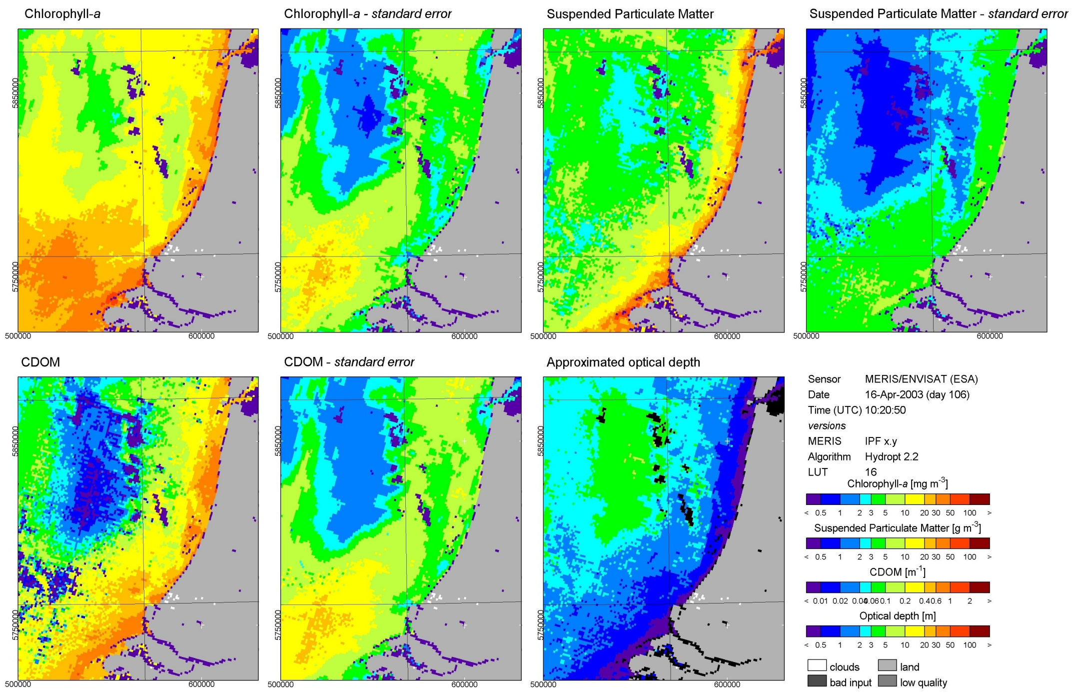

Figure 9 Water quality parameters and error products. Nearshore optical depth (approximated by $1/K_{D560}$) is limited.

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 ~ 2x2 km). The grid is coarser in the outer parts of the area included in the model (down to ~ 20x20 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.

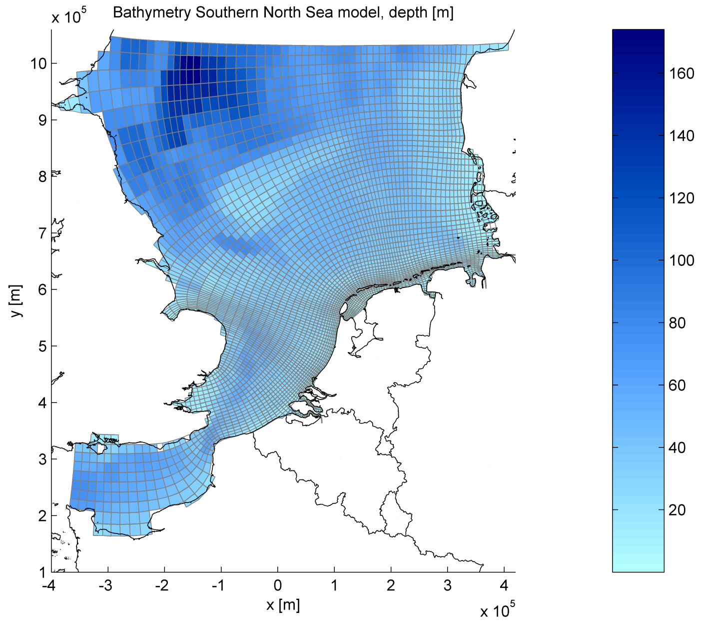

Figure 10. Horizontal grid of the Southern North Sea model applications, together with the bathymetry. The individual hydrodynamic, wave and transport models all operate on the same grid.

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.

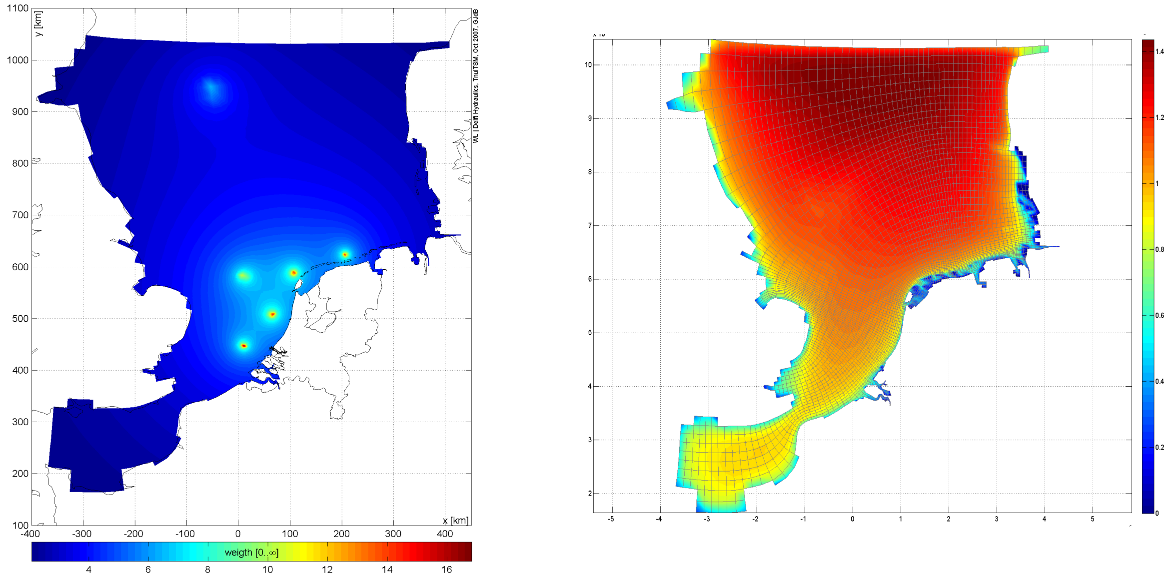

Figure 11 left: Spatial distance function related to the 6 wave buoy locations (local maxima);right annual mean significant wave height (m) for 2003 as determined by the wave model SWAN.

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 be 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.

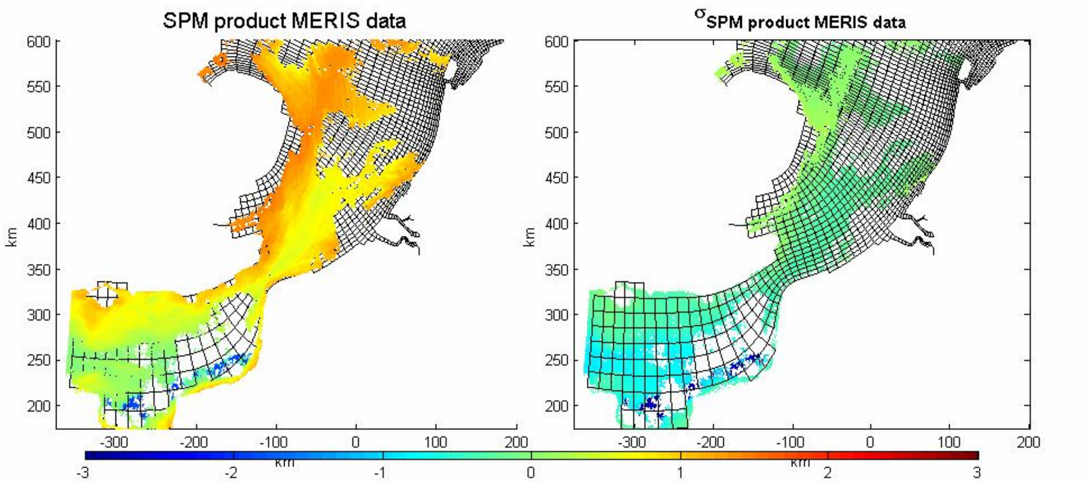

Figure 12 SPM product MERIS data and its standard deviation "zoomed" into the area of interest on the 17th December 2003 (Addressed in the text as RAW data)

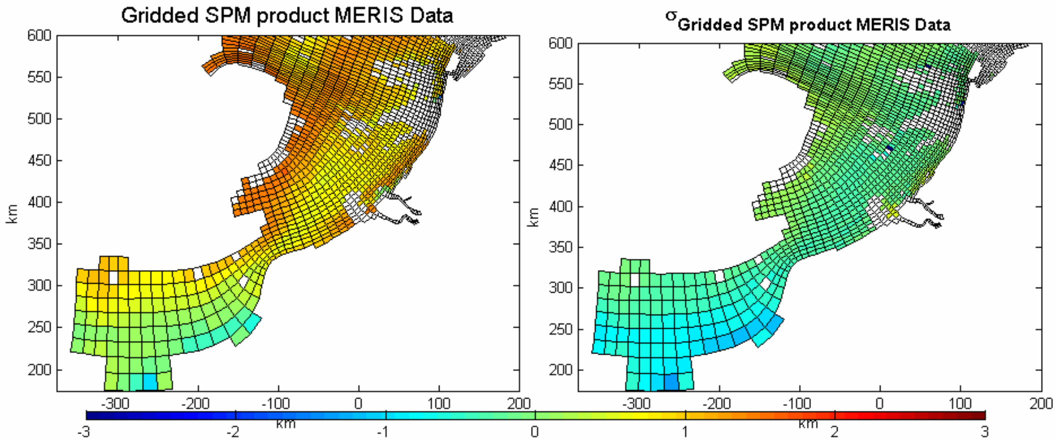

Figure 13 Gridded SPM product from MERIS data and the standard deviation of the gridded SPM on the 17th December 2003 used in the assimilation. Only the area of interest is shown in the figure.

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 girding. 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.

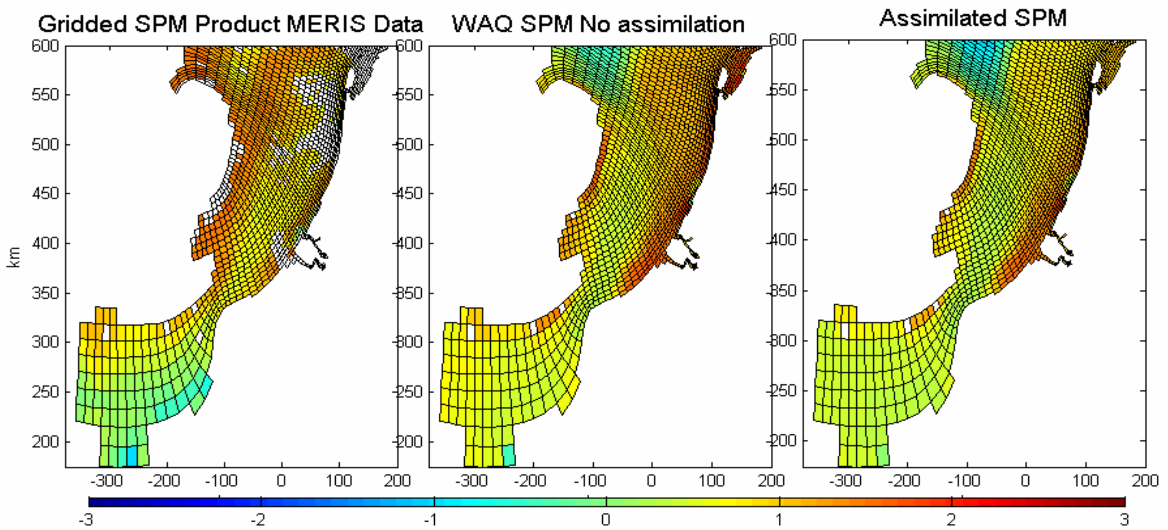

Figure 14 Gridded SPM Product of MERIS (left), Delft3D-WAQ predicted SPM without any assimilation (middle) and the SPM Estimate due to assimilation (right) on the 17th December 2003.

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.eproceedings.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 formulationand 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 Noth 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).