Using remote sensing to enhance modelling of fine sediment dynamics in the Dutch coastal zone
A. M. Y. Kamel, G. Y. El Serafy, B. Bhattacharya, T. van Kessel and D. P. Solomatine

ABSTRACT
Modelling fine sediment dynamics, including transport, deposition and re-suspension, is very complex. This led to studies that validate the modelled suspended particulate matter (SPM) based on in-situ measurements. While in-situ measurements are often sparse in time and space, satellite measurements provide us with higher spatial and temporal resolution. This information can be used to validate and enhance the model’s capability of predicting the spatial and temporal distribution of SPM. In this paper, the SPM retrieved from the MEdium Resolution Imaging Spectrometer (MERIS) on board European Space Agency’s ENVISAT spacecraft is used to carry out a thorough calibration and validation of the SPM description provided by the Delft3DWAQ model of the Southern North Sea for the year 2007. In an uncertainty analysis framework, the key model parameters affecting the SPM distributions were first identified in predefined physical regions. The sensitivity of the model to slight changes in those parameters is tested and the spatial and temporal errors compared to remote sensing images were identified and a new set of parameters has been suggested and further subjected to uncertainty to define prediction intervals of the SPM distribution at a number of locations. The so-called adapted model has been validated against independent data and has shown a decrease in errors, particularly along the Dutch coast.

Key words | Dutch coast, sediment dynamics, sensitivity analysis, uncertainty analysis, remote sensing

INTRODUCTION
Fine sediment dynamics is an important issue as it affects the environmental conditions of water systems. In addition, sediment dynamics strongly influences the morphology of the bed with regard to bed composition and bed height.

Problems associated with sediment transport along the Dutch coast due to wave breaking in the surf zone, wave and wave-induced current, always appear during the aspects of coastal management (Qinghua 2006). Fluid mud, a high concentration aqueous suspension of fine-grained sediment (cohesive sediment) in which settling is substantially hindered also constitutes a significant management problem (McAnally et al. 2007). Fine-grained suspended particulate matter (SPM) is composed of small organic and inorganic particles. It may reduce water quality since it reduces light penetration. Often deposition may impede navigation due to sedimentation in harbours and access channels. Also, the fine sediment can influence the ecology in water bodies because of the attached pollutants (Eleventh et al. 2006). In general, sediment transport is an important aspect in most coastal areas. Therefore, understanding the dynamics of sediment deposition, re-suspension and transportation is essential.

Numerical models are widely used in studying sedimentation processes. These models rely on the estimation of the values of each parameter of the model through model calibration. Most of these parameters are difficult to measure...
or show significant spatial variability (e.g. settling velocity and critical shear stress). In many cases there is an understanding of the modelled processes, which may not be detailed enough to facilitate development of accurate physically-based models and therefore leads to uncertainty in model formulation. All these issues lead to high uncertainty in model predictions. Thus, studying the sensitivity of the model to its parameters and investigating the uncertainties coming from these parameters are important in order to further improve the spatial-temporal prediction of SPM concentrations from such models.

Previous studies comparing SPM field measurements with simulated results from the numerical model based on Delft3D showed that the model is able to reproduce observed sediment concentrations reasonably well (Van Kessel et al. 2011). The model bias however differs in coastal and offshore areas (van Maren et al. 2009) in summer or winter, depending on parameter settings. Using additional sources of information such as remote sensing (RS) data would advance the development of the existing process-based fine sediment dynamics model of the Southern North Sea. Recently, RS data of the Dutch coastal area as well as in-situ measurements at some locations farther off the Dutch coast have become available.

In recent years, integrated observation-modelling efforts have been and are still being undertaken to further describe and understand the coastal system exploiting the new sources of information available (Gerritsen et al. 2000; Gayer et al. 2006; Allen et al. 2007; De Boer et al. 2009; Fettweis et al. 2007). The assimilation of RS data through state update has been presented in El Serafy et al. (2007) and further improved in El Serafy et al. (2011). Extending on this work, this paper presents an uncertainty framework and the use of RS data to estimate the significant model parameters that increase the model’s capability to better describe the SPM distribution over the whole Southern North Sea (notably the Dutch coastal zone). Results from the model using the estimated set of parameters (addressed as adapted model) are validated against in-situ measurements of SPM concentrations at a few locations. Furthermore, uncertainty analysis is used to define the prediction interval at these locations.

The paper starts with a description of the sedimentation dynamics of the Southern North Sea and the different sources of data available within the region. The research methodology and the uncertainty framework are given in detail below, in the ‘Uncertainty framework’ section of the paper, together with the validation of the results. A set of conclusions and recommendations for further research are presented in the final section of the paper.

**FINE SEDIMENT DYNAMICS ALONG THE DUTCH COAST: STUDY AREA DESCRIPTION**

The main sources of fine-grained sediment in the Southern North Sea area are the Dover Strait, the Atlantic Ocean, coastal erosion along the French and British cliff coasts, erosion of the seabed, fluvial sediment supply, dredged material from harbours and shipping channels, etc. Coastal erosion in the British Channel and the French coast produce large amounts of material every year (Vuurens 2001). Portions of these sediments settle in several sedimentation traps during the fair weather season acting as a sediment source during the rough weather. Thus, five

![Figure 1 | Sedimentation traps in the Dutch shore.](https://iwaponline.com/jh/article-pdf/16/2/458/387313/458.pdf)
major sedimentation traps are formed (Figure 1) from south to north:

- Offshore at Zeebrugge (Belgium) at the mouth of the Western Scheldt River.
- Eastern Scheldt mouth.
- Haringvliet outlet.
- The Maasmond area.
- Further north of Maasmond is the Wadden Sea along the Dutch and German coast (not shown in the figure).

The North Sea bed is formed mainly of sand and a small portion of mud that re-suspend during storms. Several researchers (e.g. Eisma & Irion 1988) have attempted to quantify sediment fluxes through the North Sea originating from these sources (Table 1). According to these studies, there is a considerable seasonal variability of the influx of fine sediments into the North Sea. Sediment fluxes originated from coastal erosion mostly occur during rough weather conditions.

Density-driven currents are created by the discharged fresh water from the River Rhine, which increases the suspended sediment concentration near to the Dutch coast. As a result of the density currents in addition to the Coriolis force, an area known as the Region of Freshwater Influence or Coastal River with a width of about 10 to 20 km is formed along the Dutch coast (WL | Delft Hydraulics 2001). The Coastal River exhibits strong vertical fresh-saline water induced stratification. Furthermore, the biological activity in the area can enhance flocculation, increasing the settling velocity and thus affecting sediment dynamics (De Boer et al. 2009).

The sediment transport model setup (ZUNO-DD)

The hydrodynamic model for the Southern North Sea was built using Delft3D on a coarse grid addressed as the ZUNO coarse grid. The model consists of three main modules: flow, wave and water quality (transport and SPM).

The model setup for the North Sea was developed by Deltares (see Cronin et al. 2009). The numerical model has a coarse grid of about 5 km by 5 km with refinements up to 500 m by 500 m at locations of importance and 12 layers in the vertical with varying layer thickness to account for the near-bed and near-surface vertical velocity gradients. The hydrodynamic model (Stelling & van Kester 1994; Lesser et al. 2004) calculates the non-steady flows and the transport coming from tidal and meteorological forcing (i.e. wind field) on a curvilinear grid. In addition, the hydrodynamic outputs (velocities, water elevations, density, salinity, vertical eddy viscosity and vertical eddy diffusivity) are used as input to the transport and water quality model Delft3D-WAQ which is used for the SPM transport computations.

A bed model was developed for another modelling study of the Markermeer in 2007. Adaptations include introduction of a third sediment fraction with much lower settling velocity, and further optimization of parameter settings.

The Delft3D modelling system computes the advection-diffusion, settling and re-suspension of SPM in three silt fractions given the transport velocities, mixing coefficients and bed shear stress adapted from the hydrodynamic and wave models. The parameterization of the re-suspension and buffering of the silt fractions from the seabed enabled a realistic description of the periodic and relatively limited re-suspension during the

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**Table 1** | Estimated fine sediment fluxes (in million ton per year) to the North Sea from different sources (Eisma & Irion 1988)

<table>
<thead>
<tr>
<th>Source</th>
<th>Estimated Flux (in million ton per year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dover Strait</td>
<td>20 to 30</td>
</tr>
<tr>
<td>Atlantic Ocean and Baltic Sea</td>
<td>10.5</td>
</tr>
<tr>
<td>Coastal erosion</td>
<td>2.2</td>
</tr>
<tr>
<td>Bed erosion</td>
<td>9 to 13.5</td>
</tr>
<tr>
<td>River</td>
<td>4.8</td>
</tr>
<tr>
<td>Total</td>
<td>46.5 to 61.0</td>
</tr>
</tbody>
</table>

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**Figure 2** | Sedimentation buffer model (adopted from Van Kessel et al. (2011)). $S_1$ and $S_2$ are bed layers of thickness $d_1$ and $d_2$. $D_1$ and $D_2$ are deposition fluxes towards the bed layers, and $E_1$ and $E_2$ are erosion flux from the layers, and $C$ is the SPM concentration.
tidal cycle and the massive re-suspension from deeper bed layers observed during high wave events. As shown in Figure 2, the sedimentation buffer model (Van Kessel et al. 2011) contains two bed layers, each of which interacts with the water column in a specific way. The first layer, denoted by S1, is a thin fluffy layer that is easily re-suspended by tidal currents. On the other hand, the sandy buffer can store fines for a longer time and releases SPM only during highly dynamic conditions, such as spring tides or storms. Both layers interact with the water column, but with different rates, depending on the different physical processes involved in either settling or re-suspension mechanisms.

The deposition towards the layers S1 and S2 is influenced by the settling velocity, $V_{\text{sed,IMi}}$ and a saturation factor, $a_{\text{IMi}}$, that distributes the flux to the seabed and depends on the concentration, $C_{\text{IMi}}$, of the inorganic fraction IMi. The main equations describing this process are illustrated below:

$$
D_{1,\text{IMi}} = (1 - a_{\text{IMi}})V_{\text{sed,IMi}}C_{\text{IMi}}
$$
$$
D_{2,\text{IMi}} = a_{\text{IMi}}V_{\text{sed,IMi}}C_{\text{IMi}}
$$

Under re-suspension events, the re-suspension flux of the SPM fraction, $E_{\text{1,IMi}}$, occurs from the two layers. For the fluffy layer, the re-suspension of the fractions is proportional to the critical re-suspension stress layer, $\tau_{\text{crSiIMi}}$, and to a re-suspension rate, $V_{\text{Res,IMi}}$, from layer S1. Then, a type of pickup formulation, $F_{\text{ResPUp}}$, is applied for the re-suspension for the buffer layer. In this situation, the fines are detrained from this layer only beyond critical mobilization conditions, $\tau_{\text{Shi}}$. $M_i/j$ is the mass of the sediment fraction $i$ in layer $j$ per surface area.

The erosion is thus mostly influenced by the critical Shields stress ($\tau_{\text{Shi}}$) and the pickup factor, ($F_{\text{ResPUp}}$). The main equations describing this process are:

$$
E_{1,\text{IMi}} = \min(Z_{\text{Res,IMi}}, V_{\text{Res,IMi}}, M_{i,j}) \left( \frac{\tau}{\tau_{\text{crSiIMi}}} - 1 \right)
$$
$$
E_{2,\text{IMi}} = F_{\text{ResPUp}}M_{i,2} \left( \frac{\tau}{\tau_{\text{Shi}}} - 1 \right)^{1.5}
$$

For the deposition and re-suspension process, four parameters were identified:

1. **Sedimentation velocity** that influences the deposition towards the S1 and S2 layers contributes to the spatial distribution of SPM; ($V_{\text{sedIMI}}$)
2. **Critical shear stress** which affects the re-suspension process from the fluffy and sandy layers; ($\tau_{\text{RCIM1}}$)
3. **Critical Shields stress** that is involved in the re-suspension process from S2; ($\tau_{\text{Shields}}$)
4. **Pickup factor** from buffer layer which implies more erosion if it decreases. ($F_{\text{ResPUp}}$)

**Data sources available in the Southern North Sea region**

The developments in data sources enable a new level of describing and understanding the physical and biological dynamics in coastal seas including SPM transport (Thorne et al. 2003; Williams et al. 2004; Davies & Thorne 2005; Widdows et al. 2005). Two main types of SPM measurements are available for the Southern North Sea, with different spatial and temporal coverage: field measurements and RS data.

**Field measurements**

Each country neighbouring the Southern North Sea (The Netherlands, Belgium, United Kingdom, and Germany) collects data at several locations. The measurements are carried out by ship-based sampling trips on regular intervals in addition to occasional data measurement campaigns. Recently, data have also been measured by optical devices moored on a floating buoy (known as smart buoys) anchored at locations of interest thus providing frequent sampling possibilities (Kröger et al. 2009). Field measurements’ properties vary depending on whether they have been obtained during measurement campaigns at sea or through devices moored to the seabed or automated in-situ monitoring buoys.

The uncertainty ranges for the data depend significantly on the measurement method. For instance, a distinction should be made between measurements with optical devices and measurements by sampling. The uncertainty of measurements can usually be estimated by studying the way the data are processed and by comparing concomitant data from different sources (van Maren et al. 2009). Part of these in-situ measurements have been used in the validation of the results shown in the ‘Validation against field measurement’ section below.
RS data

SPM is a natural constituent of the coastal waters and as such affects the colour of the sea. As a consequence, SPM can be observed by air or space-borne optical sensors (e.g. from NASA’s MODIS sensors and ESA’s MEdition Resolution Imaging Spectrometer (MERIS) sensor) (Eleveld et al. 2008). Moreover, with the arrival of reliable ocean colour RS data more frequent synoptic mapping of the sea surface SPM has become feasible (Doerffer & Schiller 2011). Figure 3 illustrates that the contrasts in the water colour in the Southern North Sea area due to suspended and dissolved matter as observed by the MODIS sensor aboard the Terra platform (Blaas et al. 2007).

Remotely sensed SPM used in this study originates from the MERIS instrument on board European Space Agency’s (ESA’s) ENVISAT spacecraft. With its 15 bands selectable across range: 390 to 1,040 nm, MERIS data give high values for the SPM concentration near the Dutch shore. This high reflectance comes from the high sediment load that might impact the atmospheric correction besides causing saturation of the water reflectance signal in the shorter wavelength bands (Ruddick et al. 2000).

The European Space Agency (ESA) declared the end of the mission for ENVISAT spacecraft and as a result, the MERIS data are not available today. Thus, we are waiting for its replacement. However, the conclusions and findings in this paper would not be significantly changed since they are directed to the model behaviour and are not necessarily dependent on data sources. The uncertainty ranges for RS data are large. These ranges depend on the measurement (monitoring) method. It depends significantly on the way the SPM is retrieved from the ocean colour RS images, which is dependent on good atmospheric correction and characterization of the high variability in Inherent Optical Properties (IOPs) (Eleveld et al. 2007). Details of the retrieval algorithm and the specification of MERIS can be found in Eleveld et al. 2008.

Furthermore, the availability of RS data depends on the weather conditions. In summer seasons (sunny weather), RS data are available with high spatial coverage. Conversely, in winter seasons (storm weather), RS data are available with less spatial coverage because of the presence of dense clouds that hinder observing SPM concentrations in the water surface. Similar to the availability of RS data, the quality (accuracy) of the data is affected also by the weather conditions (Eleveld et al. 2008). For this research the remotely sensed SPM for the year 2007 were obtained from the Institute for Environmental Studies of the Free University of Amsterdam, (VU-IVM). The RS data have very high spatial resolution in oceans 1 km × 1.2 km and in coastal waters 0.2 km × 0.3 km compared to the numerical model’s grid. Also, the RS data have very high spatial and temporal resolution compared to the in-situ measurements (Eleveld et al. 2008). In order to be able to compare the RS data with the model results, it was necessary to map the RS data to each model grid. RS data came in a raw form, which means that the data covered different areas inside and outside the study area and were composed of different kinds of data such as chlorophyll, SPM and coloured dissolved organic matter. Accordingly, it was essential to filter the non-needed data from the raw MERIS data.

The first step in the filtering process was to exclude any data that were located outside the mask that represents the limits (boundaries) of the study area. The second step in the filtering process was to remove the land and cloud pixels. The third step was to exclude the extreme values. Last step was to exclude the pixels with bad reflection values (El Serafy et al. 2011). According to the spatial...
resolution, there are several ways to map the MERIS data and each way brings different errors. For simplicity it was decided to average the values inside each model grid segment for this study. The accuracy of the retrieved SPM values per pixel is also an output of the retrieval algorithm as discussed in Eleveld et al. (2008) and varies per pixel addressed as standard deviation. The high quality of the SPM data has been extensively checked against in-situ SPM measurements and is given in Peters et al. (2008). It is assumed that on average the errors in the model are bigger than those in the data, thus making it attractive to integrate the data into the model as discussed in El Serafy et al. (2011).

**UNCERTAINTY FRAMEWORK**

The uncertainty framework followed in this paper deals with three components (Figure 4). First, the significant parameters influencing the deposition and the re-suspension mechanism were identified through the sedimentology experts’ opinion (Van Kessel et al. 2011). Through an analysis of the root mean squared error (RMSE) of the so-called reference model output compared to satellite measurements, the sensitivity of the model to slight changes in those parameters was tested to confirm and improve the understanding of the dynamics of cohesive sediment deposition, re-suspension, and transportation on the Dutch coastal zone. Within this framework, different types of model errors have been identified such as spatial and temporal errors. Unlike the previous studies, identifying the model errors in this study was done by comparing the model results with the RS data. This allowed identification of the distribution of the errors along the study area. In addition, analysis of the errors was carried out considering the spatial and temporal distribution of these errors. Carrying out this step enabled us to observe the reference model performance efficiently, which is not the case if we only compare the model results with the sparse in-situ measurements. Accordingly, from this analysis, a new set of parameters has been suggested, and used in the so-called adapted model. This adapted model has been validated against independent data.

Finally, the adapted model has been subjected to uncertainty analysis from which the bandwidth of model uncertainty, expressed in terms of the prediction interval, has been identified for different seasonal periods and different spatial zones. This analysis has resulted in recommendations for further targeted model improvements.

**Sensitivity of the model output to identified parameters**

According to the sedimentology experts, the most significant parameters are the parameters that have influence on the deposition mechanism and on the re-suspension process as have been described in the sedimentation buffer model earlier in this paper. Since in any calibration procedure, the target is to minimize the residuals between the model output and the measurements, the sensitivity analysis here focused on the effect of small changes in the four key parameters on the residuals (i.e. between SPM distribution as an output of the model and the MERIS satellite data). The bias and RMSE are used as a measure for the residuals. Moreover, to be able to synthesize the effect of incremental changes of the parameters on the model output, spatial and temporal aggregations of residuals were carried out. The dynamics of the Southern North Sea varies significantly with its physical characteristics in different regions (e.g. different responses near the shore or farther offshore). Accordingly, it was decided to carry out this experiment.
by identifying different regions in the study area. The regions were identified based on available domain knowledge and expert opinion (Figure 5).

For this sensitivity analysis, an ensemble of eight members (the choice is due to computing capacities) was created for each of the four parameters. The ‘one parameter at a time’ approach to sensitivity analysis (Saltelli 2004) was followed and the effect of each parameter was examined separately. The sampling was carried out within the physical limits of values of each parameter for the North Sea (Van Kessel et al. 2011). A simple method for sampling the parameters was chosen. Assuming a commonly used distribution for uncertainty, a normal distribution of the parameter values and choosing the parameter value in the reference simulation as the mean and the standard deviation as 10% of the mean, parameter values were sampled. Choosing another distribution would not alter the strategy presented here. The 10% is a rough estimate of the uncertainty on the parameter. This choice does not directly alter the conclusions of the results. The uncertainty should be big enough to show an effect on the model output but not so unrealistically big that it provokes irregularities. Taking the standard deviation in the range of 5–15% of the parameter value is still a reasonable choice. In total 33 simulations were carried out.

For the reference simulation, the sedimentation velocity was different for each sediment fraction. The sedimentation velocity and its ranges, given by the experts and shown in parentheses, are 10.8 (5.4–16.2) m/day for the first fraction (medium fine size), 86.4 (25.9–147.0) m/day for the second fraction (coarse grain size), and 0.1 (0.07–0.13) m/day for the third fraction (very fine grain size). Similar to the sedimentation velocity, the critical shear stress was different for each sediment fraction. It was 0.2 (0.06–0.34) Pa for the first and the second fractions, and 0.1 (0.03–0.17) Pa for the third fraction. The Shields shear stress for re-suspension pick-up was 1.5 (0.5–2.5) Pa, and the re-suspension pick-up factor was $3.5 \times 10^{-7} (1 \times 10^{-7} - 8 \times 10^{-7})$ kg/m$^2$/day.

For each simulation, the model outputs were compared with RS data for the year 2007. The comparison was done by calculating the residuals (differences between the SPM concentrations at the surface from the model and the RS data) for each zone shown in Figure 5. The residuals were aggregated for each zone for different seasons and for the entire year. As a measure of the deviation of the model output from the RS, the RMSE is shown in the figure. The annual average bias was computed for each zone for each parameter as a measure of the overestimation or underestimation of the model with respect to the RS data. The bias was computed as the difference in the SPM value from MERIS and the model, averaged over the year. As a result, a negative bias means overestimation by the model. One of the results of the sensitivity of the model to changes in the sedimentation velocity is presented in Figure 6.

Figure 6 indicates that the behaviour of the SPM with respect to changes in the sedimentation velocity is approximately similar for each zone. However, the changing percentages (i.e. the errors in simulations with new parameter values compared to the errors in the reference simulation outputs) are different from one zone to another. Increasing the sedimentation velocity for the first fraction from 10.8 m/day to 15.1 m/day reduces the RMSE by 12% in zone 5, 6 and 8, and by 5% in zone 1, 2 and 4, and reduces the bias by 60% in zone 6 and 7, and by 50% in zone 1 and 8. Higher sedimentation velocity allows for faster settling of sediments, which causes a decrease in the SPM concentrations in the water column and vice versa. From Figure 6 it is also obvious that, on average, the model overestimates
the SPM concentration for all zones except for zone 4. The maximum bias and RMSE is in zone 7 and 8 (zones with the influence of fresh water discharge), which is the area of high influence of the sedimentation from the River Rhine. Therefore, the model performance could be improved in areas of high concentration. The obtained results are comparable to the results from van Maren et al. (2009).

The seasonal variability of the sensitivity of the model to sedimentation velocity was also examined. The following four seasons were identified: winter (December, January and February), spring (March, April and May), summer (June, July and August), and autumn (September, October and November). For zone 4 (near the British coast) the model underestimated in the autumn and winter, and overestimated in the spring and summer. It is worth mentioning that this sensitivity is used not only to define and examine the effect of the changes of a parameter on the model output but also to consider the possibility of finding an optimal global parameter set by reducing the residuals with the MERIS data. By reducing the bias and the RMSE, an indication of the order of magnitude of the global parameter can be reached. It is thus concluded that the optimal sedimentation velocity seems to be lying outside its acceptable ranges and the parameter values used in the model are quite acceptable for a good model performance.

Similar to the above the sensitivity of the model to the parameter critical shear stress was investigated and the results are shown in Figure 7. From Figure 7, it is concluded that the effect of the incremental changes in the critical shear stress for the first fraction is only affecting a few zones such as 6, 7, 8, 9 and 2. Those zones are along the coast with a well-mixed regime with high turbidity and shallow depth. The re-suspension within this region depends very much on exceeding this critical shear stress value. Due to the presence of the regime if we increase the critical shear stress, less suspension in the water will occur, this will result in a decrease in the SPM in the water. In the offshore regions and at the surface layers, this effect is not observed (i.e. the SPM surface layer is not affected by the critical shear stress due to stratification and or partial mixing).

Increasing the critical shear stress for the first fraction from 0.1 to 0.15 Pa reduces the error biases by 22% in zone 7 and 9 and reduces the RMSEs by 6% in zone 6 and by 4% in zone 2. However, like the sedimentation velocity, the optimal critical shear stresses for most of the zones could not be identified and no influence of seasonality was observed. Since the model uses only a set of global parameters and since the effect of changing this parameter (critical shear stress) was observed only along the shore, this parameter was concluded to be not among the
important ones. If in the future different parameter values for different regions are considered then this parameter may play an important role.

The variation in the average errors expressed in RMSE and bias for all zones with changing the Shields shear stress for re-suspension pick-up is shown in Figure 8.

Unlike the critical shear stress, the effect of the Shields stress, although pronounced at coastal zones, is also visible at all other zones. Looking at Equation (2) defining re-suspension from the second layer, it is clear that at all zones, the Shields stress and the factor of re-suspension are the two governing factors with an index of 1.5 and are

Figure 7 | The yearly average bias (left) and RMSE (right) in each zone is plotted against the change in the critical shear stress for re-suspension (Pa) for the first sediment fraction. The vertical line indicates the value of the reference simulation.

Figure 8 | The yearly average BIAS (left) and RMSE (right) in each zone is plotted against the change in the Shields Shear Stress (Pa). The vertical line indicates the value of the reference simulation.
dependent on the weather conditions. If the weather is calm, the re-suspension happens from the first layer. If the weather is rough, re-suspension happens also from the second layer where the critical Shields stress is a governing factor at all zones. The effect, however, is different from one zone to another. This is also reflected in the percentage change in the bias and RMSE due to increasing Shields shear stress. For example, increasing the Shields stress from 1.5 to 2.5 Pa reduces the bias by 90% in zone 3, 6 and 9 and by 50% in zone 5 and 8 and reduces the RMSE by 21% in zone 5 and by 16% in zone 6, 7, 8 and 9. On the contrary, the bias is increased slightly in zone 2 and 4. It is also noted that the effect of this parameter is higher in the autumn period where rough weather conditions in November were recorded. By changing this parameter, the model performance can be significantly affected at all zones but more pronounced along the coastal area.

The variation in the average error for all zones with changing the re-suspension pick-up factor is shown in Figure 9.

As expressed in Equation (2), the re-suspension in the water column from the second layer is directly proportional to the re-suspension pick-up factor. As this factor increases, the SPM in the water column increases. The effect of this parameter is reversed compared to the effect of the other parameters such as sedimentation velocity, re-suspension critical stress and the Shields stress on the SPM concentration. This is also reflected in the sensitivity of the model output to the changes in the parameters. It is also concluded that this parameter affects SPM values in all zones with different intensities. Decreasing the re-suspension pick-up factor from 3.5 kg/m²/day to 1.0 kg/m²/day reduces the bias by 90% in zone 3 and 9 and by 70% in zone 6 and 7, and reduces the RMSE by 18% in zone 5 and 9 and by 16% in zone 6, 7 and 8. Like the Shields stress, the effect of this parameter is stronger during rough weather conditions. It has to be mentioned that one should be careful changing both the Shields stress and the re-suspension pick-up factor at the same time, since their effects are complementary.

In general, the comparison between the model results from the sensitivity analysis gives an indication that the model is sensitive to some of the parameter values more than others. It also appears that limited improvements of the model’s accuracy are possible for some areas and in some seasons. For example, the model’s accuracy would improve in winter and autumn by estimating the re-suspension pickup factor and/or the Shields stress. The model’s accuracy would improve in all seasons by better estimating the sedimentation velocities. In addition, differences in the model’s accuracy in the spatial scale with changing parameter values were observed. It was noticed that the
model’s accuracy would improve by estimating the re-suspension critical shear stress at the coastal areas at shallow depth rather than at areas such as the British coastal zone.

**Analysing the performance of the adapted sediment transport model**

According to the sensitivity analysis detailed in the previous section and the understanding of the behaviour of the model with respect to the changes in the identified parameters, an improved set of global parameters were estimated (Table 2).

The model with the estimated set of parameters is referred to as the *adapted* model. The outputs of the *adapted* model were compared to the MERIS data to check if the model performance has been improved with respect to the data that were used in the estimation process. The RMSE and bias, averaged over the year, were calculated per zone and compared to the reference model (Table 3).

It is clear from the summary in the table that a considerable improvement was obtained by changing the model key parameters at all zones except for the bias at zone 2 (near the British coast) and zone 4 (German Bight). As for the rest of the zones, the *adapted* model is better than the reference model as the bias was reduced by more than 50% in all zones and the RMSE decreased more than 20% in the along-shore zones and on average 6% in other zones.

Furthermore, the RMSE has been calculated for each season. The MERIS image can vary from one season to another due to clouds. If there are no clouds, it is said to have a high coverage and vice versa. Although it was expected that the MERIS image coverage for the region would play an important role in this methodology, it was not obvious from the average seasonal improvements that link with the coverage. The improvements in all months were almost the same. It is also worth mentioning that this conclusion is based on 2007 where the coverage within the seasons identified here is more or less equal. It would be different if there were no data for estimation in the whole season (3-month period) which is a rare situation. In that case it is advised then to consider several years of data for the estimation process suggested here. The average SPM distribution for February (lower coverage) and June (high

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**Table 2** | Estimated parameters used kg/m²/day in the adapted model resulting from the sensitivity analysis

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Critical Shields stress (Pa)</th>
<th>Sedimentation velocity for different fractions (m/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Critical shear stress (Pa)</td>
<td>Medium fine</td>
</tr>
<tr>
<td>Estimated</td>
<td>1.7</td>
<td>0.3</td>
</tr>
<tr>
<td>Reference</td>
<td>1.5</td>
<td>0.2</td>
</tr>
</tbody>
</table>

**Table 3** | The mean annual errors expressed in bias and RMSE from reference model and adapted model for each zone

<table>
<thead>
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<th>Error</th>
<th>Bias (mg/l)</th>
<th>RMSE (mg/l)</th>
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</tr>
<tr>
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</tr>
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</tr>
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</tr>
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</tr>
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</tr>
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</tr>
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coverage) show that the adapted model’s predictions are closer to the MERIS data (visual inspection), see Figure 10. From the figures, it seems that the boundary conditions are overestimated at the left boundary and are affecting the SPM values in the channel. This might cause the model behaviour to be poor in both the reference and the adapted model cases. The boundary conditions are climatology values of the SPM, and other months show no overestimation (Suijlen & Duin 2003). However, it is recommended to improve this choice of the boundary conditions which would improve the model behaviour. For the methodology and the results, if the boundary conditions are slightly overestimated or underestimated that would not alter the conclusion on the strategy adopted here in the paper.

Validation against field measurements

In order to validate the behaviour of the adapted model with respect to independent data, the model output was compared to field measurements available in the region for the year 2007. The field measurements were taken from 16 observation points covering approximately the whole study area.

The validation was carried out with the data from all observation stations in Figure 11. Results from four observation points at 2, 10, 20 and 70 km offshore of Noordwijk are shown. Similar to the previous conclusion, the behaviour of the adapted model was better near the shore (Noordwijk 2, Figure 12(a)). Further offshore, the adapted model, compared to the field values, underestimated the SPM values (Noordwijk 10, Figure 12(b)). At 20 km offshore of Noordwijk, the model slightly underestimated the SPM (Figure 13(a)) and, the performance of the model deteriorated at 70 km offshore of Noordwijk (Figure 15(b)). The performance of the model is comparable at other stations as well. Therefore, it can be concluded that the adapted model is improved near the shore and deteriorates in the offshore regions. Improving the model for the offshore regions will be a future research task.

From the figures, it can be seen that the SPM concentration of the adapted model is always lower than the reference model. It also can be seen that most of the SPM concentrations obtained from RS data are lower than the in-situ measurements. Since the sensitivity analysis was done with the MERIS data, the adapted model is biased more towards lower concentrations. Future recalibration experiments should involve field data as well. Furthermore, the model skill should be also evaluated not only with respect to near-surface SPM concentration, but also with respect to near-bed SPM concentration, bed composition, yearly long-shore sediment flux, net deposition, tidal, neap-spring and seasonal variations etc.
<table>
<thead>
<tr>
<th>Source</th>
<th>Abbr.</th>
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<th>Abbr.</th>
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<td></td>
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<td></td>
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<td>R12</td>
<td>Terschelling 4</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 11 | Validation stations of the Rijkswaterstaat (RWS, Ministry of Infrastructure and Environment, The Netherlands) are in green dots and MUMM (Management unit of the North Sea mathematical models, Belgium) observation stations in blue and CEFAS (Centre for Environment, Fisheries & Aquaculture, UK) smart buoys in red. The abbreviation in the right hand panel is tabulated in the left panel. The circled stations are the so-called Noordwijk transect stations. Please refer to the online version of this paper to see this figure in colour: [http://www.iwaponline.com/jh/toc.htm](http://www.iwaponline.com/jh/toc.htm).

Figure 12 | The SPM concentrations from the reference simulation, adapted model, MERIS data, and the in-situ measurements at Noordwijk 2 (upper panel) and Noordwijk 10 (lower panel) observation points.
Other parameters affecting the bed composition should be included in future recalibration.

**Uncertainties and prediction intervals of the adapted model**

The focus of this phase is investigating the uncertainties in the numerical model coming from the model parameter estimations. The essence of the model uncertainty analysis is finding the 90% prediction interval of the model at several locations. The prediction interval is formed by the 5 and 95% quantile of the empirical distribution of the model outputs obtained for the sampled parameter vectors, and it is done for each time step (see e.g. Solomatine & Shrestha 2009). It will be useful to use different methods and/or to extend the simulation number to have more realistic assessment of parameter uncertainties but due to the computational burden, the uncertainty analysis was done in a limited way. In the uncertainty analysis, the same four key parameters used in the sensitivity analysis were used. Unlike the sensitivity analysis, changing the parameters was not carried out using a one-at-a-time approach, but was done randomly drawn from a distribution. This would stress the combined effect of the changes in the parameters and the influence of that on the model output. The Latin Hypercube Sampling (LHS) (see e.g. van Griensven 2005) method was used for sampling these parameters. This method is often used in uncertainty analysis studies. The principle of this method is in dividing the range of each parameter into a chosen number of equally probable intervals. The number of these divisions should be equal for all parameters. The probability distribution used in this division is the cumulative probability distribution from a normal or a uniform distribution. The last step is to generate randomly only one sample (value) in each row/column to cover the parameter domain. Figure 14 shows an example of applying the LHS method to sample two parameters.
By knowing the range for each parameter and desired number of samples, the LHS was used to generate 100 ensembles for the eight parameters. The relatively low number of ensembles used was due to the computational time limitation (one model run was taking more than an hour).

The approach used to analyse the model performance here is similar to the one used in the sensitivity analysis. However, the uncertainties were not assessed comparing the results to RS data only but also to the in-situ measurements. By collecting the modelled SPM concentrations after the 100 simulations at the observation points and forming 90% prediction intervals (PI) for the modelled SPM concentrations after calculating 5% and 95% quantiles, these prediction intervals were plotted for each observation point separately at all locations shown in Figure 11. Figure 15 shows the prediction intervals at locations Noordwijk 2, 10, 20 and 70 together with the field measurements and the MERIS measurements. If the measurements lay within this interval that means that the model under those uncertainties can reproduce the measurements.

The prediction intervals of the model outputs are larger at Noordwijk 2 (close to shore) and Noordwijk 70 (70 km offshore) than that at Noordwijk 10, and 20. The large PI is due to the sensitivity of the SPM to those specific parameters. However, since in this research a global parameter set was estimated and since the SPM concentrations along the shore are much higher than those offshore, more weight was given to the along-shore regions in the estimation than the offshore regions. This confirms the improvement at Noordwijk 2 station and the deterioration that happens offshore. Further, the model seems to manage reproducing similar SPM concentrations...
Figure 15 | The prediction interval for SPM concentrations at 2, 10, 20 and 70 km offshore of Noordwijk observation point.
concentrations to the measured ones for Noordwijk 10 and 20. The observation values lie within the PI at most of the observation points. On some occasions, the model is over- and/or under-estimating the SPM concentrations as indicated at the two observation points Noordwijk 10 and Noordwijk 20. The model generally manages to mimic the variability of the SPM concentrations. As pointed out earlier, comparing the model outputs with each type of data (in-situ measurements and RS data) leads to different results (Kamel et al. 2012). Note that the time resolution of the field measurements at the traditional observation points is too limited.

CONCLUSIONS AND RECOMMENDATIONS

In this paper, the SPM retrieved from the MERIS instrument was used to carry out a thorough validation of the SPM prediction provided by a numerical model based on the Delft3D-WAQ modelling tool for the year 2007. In an uncertainty framework, the key model parameters affecting the SPM distributions were first identified. The sensitivity of the model to changes in these parameters was tested, and the spatial and temporal predictions were compared to SPM values from RS images. From this analysis, a new set of values of the parameters has been suggested, and the adapted model has been tested against independent field data. Prediction intervals were computed at a number of locations.

Within the uncertainty framework steps have been identified: sensitivity analysis, estimation and uncertainty analysis. The sensitivity analysis provided the means to confirm the significance of the model parameters identified by the experts. Such an analysis confirmed the model’s capability in representing the SPM distribution in the Southern North Sea. It allowed the identification of the critical regions within the North Sea where the model can still be improved. From the sensitivity analysis, it is concluded that the critical Shields stress and the re-suspension pickup factor have the highest impact on the prediction accuracy in all regions followed by the settling velocity. It was also concluded that the critical shear stress would influence the prediction more in the coastal zones than it would in other zones. Also, the influence of the weather conditions, together with the overall coverage of RS data, are captured in the monthly evolution of the most important parameters.

Based on the analysis of the sensitivity results expressed in bias and RMSE, a new set of values of parameters was estimated. Since the model deals with a single set of parameters applicable to all regions, the performance of the model at different regions of the North Sea was optimized to achieve a global improvement. The estimation process was based on finding a trade-off between the bias and the RMSE at all regions. Due to the estimation, improvements were achieved at almost all regions. The adapted model is better than the reference model as the bias was reduced by more than 50% in all zones and the RMSE decreased by more than 20% in the along-shore zones and on average 6% in other zones.

This was also confirmed by validating the results with field measurements. From the validation, the improvements of the SPM concentrations at locations along the shore are confirmed. However, a slight deterioration is observed in the offshore regions. It is recommended, however, to estimate a set of parameters per region to ensure optimal reduction of errors. Although the obtained results correspond well with the dynamics of the waters, still, a more in-depth interpretation of the results should be performed.

Finally, uncertainty analysis is used to examine the prediction capability of the adapted model with respect to combined effects of the parameters. The LHS method was used for sampling these parameters. At the observation points, 90% prediction intervals for the modelled SPM concentrations are plotted against time, together with the available MERIS data used in the estimation and the field measurements as an independent data source. Most of the measurements are within this interval. That means that the model under those uncertainties can reproduce the measurements. Also from those results, the improvements achieved at the stations and regions along the shore and the reasonable results at intermediate distances from the shore and the slight deterioration that was observed at offshore regions, were confirmed with argumentation. In general, the technique did not reveal any unacceptable behaviour of the model. The model generally manages to mimic the variability of the SPM concentrations with this new set of parameters. It has to be stated however that due to the computational limitations the number of simulations conducted was not enough to
make quantitative conclusions about the statistical significance of the model uncertainty estimates.

Further improvements can be achieved by including both MERIS data and field measurements of high frequency such as smart buoys into a formal estimation process for spatial variable parameters. It is also suggested to carry out a several year window analysis with such an uncertainty framework to capture the temporal variability of the system. Finally, since every source of data is retaining its own uncertainties, it is suggested to take into account in further research the uncertainties associated with different sources of data uncertainties and model uncertainties. This can be easily included in the framework presented in this paper.

REFERENCES


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