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RIKZ, Den Haag

Statistical methods to assess the impact of MV2 on SPM along the Dutch coast

Results of WP 3 & 5

Report

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Meinte Blaas, Henk van den Boogaard

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ABSTRACT:

This document is reporting the results of work package 4 of the project *Baseline Silt PMR* (RKZ 1661). Hypotheses are formulated, guided by the identified possible effects of Maasvlakte-2 on the transport and distribution of SPM in the Dutch coastal zone (Winterwerp, 2006) These hypotheses can be tested using standard statistical methods and thus provide methods to identify possible future changes in the system. Also a methodology is presented that aids to assess whether any change that may be observed is due to MV2 or not:

- Divide the Dutch coastal area into four areas : (1) an area directly surrounding the Maasvlakte 2 (MV2) which is mainly considered as a source of possible changes in the SPM transport (2) a reference area south-west of the MV2 where only autonomous changes are expected (3) two areas north of the MV2 (Holland coast and Wadden area) where both autonomous and MV2-related changes may occur.
- Use data available from these areas (measured during t_0 and t_1) to assess whether or not significant changes in the mean and in derived statistical properties of relevant measures for SPM transport have occurred.
- Design and analyse system relations between various measures of SPM transport or forcing conditions, and within and between the various areas. In this way, conclusions can be reached on whether or not any observed change is due to MV2.

For each area, key variables are identified (based on the inventory by Blaas et al, 2006) and specific hypotheses and methods to test these are presented.

Finally, time series of two transects (Callantsoog and Noordwijk) are analysed in more detail to evaluate the test of the hypothesis that no change in the long-term mean of these series has occurred. It is concluded that both variance and sample correlation are high in the SPM concentration time series which both reduce the accuracy to detect changes in the mean. Reduction of the variance and auto-correlation is feasible by including information of the SPM-affecting conditions (in particular waves and tidal currents). The development of such correction models and the benefits of their application profit much from the availability of high-frequency input data and SPM data. The typical autocorrelation time of uncorrected SPM signals of about a week can be reduced by a factor of four.

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Contents

1 Introduction

Following the description of the SPM transport in relation to the extension of the Maasvlakte (MV2) in the WL | Delft Hydraulics report Winterwerp (2006), possible changes in the SPM distribution and transport due to MV2 have been be identified. This has been done in terms of cause-effect relations as far as the present understanding of the coastal system allows. In the present report we will formulate hypotheses related to these possible anticipated changes that can be tested using standard statistical methods and thus provide methods to identify possible future changes in the system. Also we will present methods that are useful to assess whether any changes that may be observed are due to MV2 or not.

First we will shortly reiterate the main conclusions of Winterwerp (2006) combined with the main results from four recent numerical experiments on the effect of MV2 on silt concentrations over 3 full years and a 14-day spring-neap repeat period (Van Kessel et al, 2006). It should be kept in mind that these numerical model experiments represent the reality in a very limited sense (e.g., effects of waves, sediment buffering in the bed are not present). Therefore the model results are merely used to obtain a qualitative sense of possible changes and are only considered in addition to the review by Winterwerp (2006).

Secondly, we will introduce the basic hypotheses and related assumptions, based on our present understanding of the system. Then we will detail the hypotheses for specific geographic areas in the coastal system, discuss the related key variables and elaborate on the methods by means of examples or test cases to give indications of practicability.

For each hypothesis the a priori expectation is formulated based on current insight in the system relations. For every entry at least the main variables related to SPM is presented. Main variables are directly related to the principle quantity of interest: the residual flux of SPM in the Dutch coastal zone towards the Wadden Sea. Main variables are mostly (measures for) SPM concentration and current velocities. When appropriate also auxiliary variables are listed that may be investigated as well to corroborate or explain conclusions with respect to the main variables. Auxiliary variables are more indirectly related to SPM transport in the coastal zone: either they represent forcing conditions (such as waves, winds) or source conditions (river discharges and loads, disposed dredged sediments). The selection of the key variables (main and auxiliary) has been guided by the findings of the data inventory and evaluation presented in the companion report by Blaas et al, 2006.

In Chapter 8 examples are given of the application of statistical tests of the mean of several time series. In Chapter 9 conclusions are presented.
Appendix A discusses into more detail the logic applicable to the approach we propose and the conclusions that can be drawn following the rejection or acceptance of certain hypotheses. Appendix B presents in further detail the technical aspects of the statistical models and analysis methods.

At this stage, we cannot take into account all details of the properties of the data possibly used (amount, sampling density, spatial distribution, completeness, quantity, quality, etc.). At present the definition of appropriate procedures is the main issue. In a later stage, it will have to be verified in further detail which subsets of data available are suitable for testing of the hypothesis or formulation for specific statistical models. A companion report to this report is the inventory of data available and possibly of use in the methods (Blaas et al, 2006). Eventually the information of both reports will be combined in the follow-up activities that consist of an evaluation (cost-benefit analysis) of methods and recommendations for additional measurements or modeling techniques.

2 Possible changes due to MV2

From Winterwerp (2006) it can be concluded that the possible changes in the coastal system cause due to the MV2 are partly of localized nature. Changes in patterns of currents and waves due to the new geometry of the mouth of the Nieuwe Waterweg are anticipated anyhow. Because the geometrical change of the mouth of the Nieuwe Waterweg, the location, initial mixing and tidal pulsation of the fresh water plume will be affected. Finally, an increase in residence time of Haringvliet water south of MV2 and the abovementioned changes in current and wave conditions may change the phasing of SPM availability in the coastal region. In the following we focus on the possible consequences of these local changes for the larger-scale SPM-transport in the entire Dutch coastal zone and western Wadden Sea. These possible consequences are summarized below. The likelihood and magnitude of the changes is unknown but they serve as guideline to the methods discussed in this report.

The following impact of MV2 on the transport-related parameters of SPM along the Dutch coast towards the Wadden Sea is considered possible:

I. A change in cross-shore SPM distribution close to the coast: a decrease close to the coast and higher SPM-concentrations further offshore[1].

II. A decrease of about 3 to 10% in the nearshore, residual, northward SPM flux off the Holland coast

III. A decrease of about 2 to 10% in the annual mean SPM concentrations in the western Wadden Sea due to the redistribution of SPM in the coastal zone.

IV. An change (most likely a decrease) in temporal variations of SPM because of buffering of SPM in the Haringvliet mouth and larger residence times of Haringvliet fresh water south of MV2.

[1] *Note that not all numerical results show the same qualitative picture, in some occasions inshore values may increase south of IJmuiden, whereas they still decrease north of IJmuiden.*

3 Approach, null hypotheses

3.1 Introduction, presumptions

In order to assess whether changes in the SPM conditions have occurred between sets of data collected before and after MV2, hypotheses are formulated. These hypotheses can be tested using statistical techniques. Only given these hypotheses and the statistical properties of the data sets, an objective statement can be made on the statistical significance of an apparent change. In order to not only make statements about changes in the conditions but also to aid to discriminate between effects due to MV2 and other causes, a methodology is presented based on the general propagation of SPM-related information in the coastal system and the anticipated extent of MV2 effects.
Before we discuss the hypotheses, the scope to which the hypotheses apply and a number of presumptions have to be put forward. These considerations are all based on the present understanding of SPM transport in the Dutch coastal zone as it is now. In future the development of the coastal system may require adjustments of the details of the presumptions (e.g. definition of the extent of certain areas) but will not change the general concept.

3.1.1 Scope

In the present study, only the physical cause-effect relations related to SPM concentration distributions in space and time and to transport (fluxes) of SPM are of relevance. The effect of changes in SPM concentration on the is explicitly not within the present scope. Also, transport of fish larvae and consequences of possible changes in SPM transport for siltation of harbor basins etc are not the focus. Siltation data may serve as a proxy for SPM transport, though, if considered relevant.

The area of interest is the Dutch North Sea coast and western Dutch Wadden Sea (extending from the Marsdiep and Aflsluitdijk to the Schiermonnikoog watershed). Spatial scales of interest are at least a few hundred meters (e.g. related to concentration distributions, given available data), maximum spatial scale in cross-shore direction is about 100 km (i.e. typical maximum length of monitoring transects), in longshore direction the maximum distance relevant is from Dover Strait to the Wadden Sea. Spatial aggregation of observations, in particular over one or more tidal basins in the Wadden Sea, is feasible.

The minimum timescale of interest is a month (again, given the nature of available observational data and the questions of interest), the maximum realistic timescale is on the order of decades.

3.1.2 Information propagation

Generally speaking, the propagation of disturbances in the SPM transport, when averaged over a timescale of months or longer is from south to north along the French, Belgian, and Dutch coast. Hence, disturbances due to MV2 will on average propagate northward as well which will help defining a future reference area. It should be noted that there will be an area of direct influence around (also south of) MV2 that is affected by MV2 anyhow. This is not the area of eventual interest, but this area is only considered as the source of changes possibly observed further north. Based on numerical model results the southern boundary of this area is expected to be located south of the Oosterschelde. The location of the northern boundary is dependent on to what extent changes observed in future are considered trivial and due to MV2. In practice one may consider the position of the Ter Heide transect as the boundary. Because effects of MV2 are expected to propagate northward on the long term, there is an area south of Oosterschelde where effects of MV2 will not be discernable, we consider this the reference area. This area is located in an along-coast zone of about 100 km wide extending from Zeeland (south of Oosterschelde), along Belgium. As long as the long-term mean propagation of perturbations does not reverse (i.e., for all but the most extreme climatic changes) this holds true.

3.1.3 Zonation

Based on the concept of long-term mean information propagation the following zones can be identified (see also Figure 3-1)

A. A reference area, south of the Oosterschelde, extending towards Dover Strait where no effects due to MV2 are expected and as such serves to assess autonomous changes.

B. The zone in the direct vicinity of the Haringvliet and MV2 which we consider as a source area of perturbed SPM-transport signals. This area is considered without going into details of changes within this area.

C. The possibly perturbed area north of MV2

D. The possibly perturbed area of the western Wadden Sea

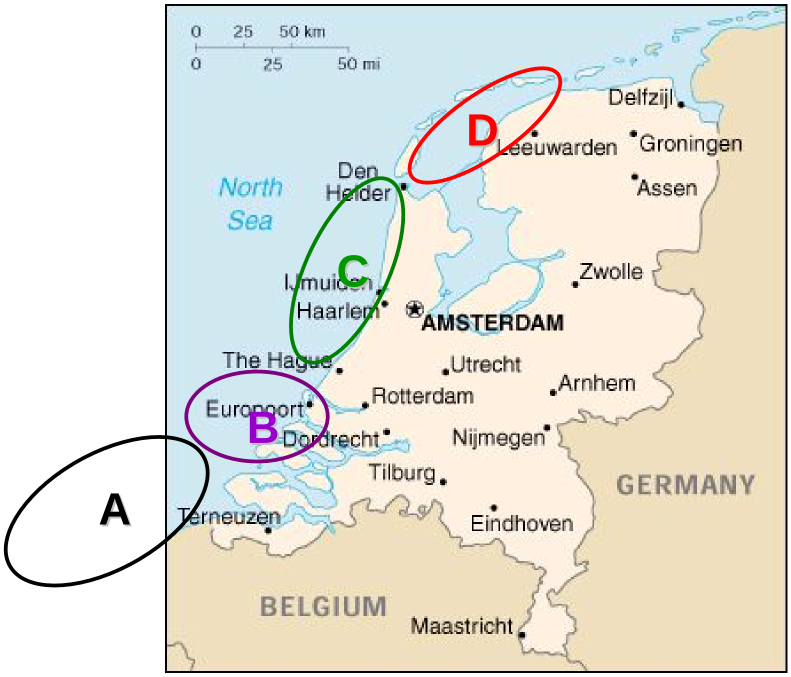

Figure 3-1 Zonation in the Dutch and Belgian coastal zone to aid the distinction of autonomous changes and possible MV2 effects in future. Contours are approximate indications of the extent of the areas.

3.2 Null hypotheses in general terms

Here we formulate the null hypotheses in general terms. They are formulated in a rather formal way such that they can be subjected to statistical testing. The hypotheses will be made more specific in the subsequent sections for each individual area relation.

I. There is no notable change in SPM-related conditions in the "unperturbed area".
II. There is no notable change in SPM-related conditions in the Dutch coastal zone north of the MV2 nor in the western Wadden Sea.
III. The system relations that describe (statistically) the propagation of information from south to north or the relation between forcing conditions and SPM fluxes or concentrations do not change notably. Hence, system functions can be defined (either within a particular zone or between zones) related to SPM transport and they do not change due to MV2.

The term 'SPM-related conditions' refers to either SPM fluxes derived from observations of concentrations and velocities or to measures for SPM concentration (the main variables) or to the auxiliary variables such as wave conditions. The hypotheses can be tested separately for the main and auxiliary variables. The distinction of different main variables and auxiliary variables is further explained in the introduction of the data inventory report (Blaas et al, 2006). The 'conditions' mostly refer to physically sensible statistical properties such as the long-term mean, median or modus, quantiles, exceedance frequency etc., but also relevant time scales (of along-coast time lags for example). For sake of the discussion most often the long-term mean can be thought of in this report but the methods are certainly not limited to this quantity.

By testing hypothesis III a distinction can be made between autonomous changes and MV2-effects. An important assumption therefore is that conditions in the "unperturbed area" relate to those in the areas north of the MV2, *i.e.* there are transfer functions relating the unperturbed area to the area of eventual interest.

It should be noted that the way the hypotheses are formulated does not necessarily reflect the a priori expectations. They are formulated to yield mathematically testable expressions.
Besides, formally, a hypothesis can only be rejected or not rejected on statistical grounds, given confidence levels. Strictly speaking, 'not rejected' does not imply that the statement of the hypothesis is 'true' or 'accepted'. It is merely not possible to reject it with sufficient confidence given the information and tools available. Nevertheless, in this report we will generally follow the pragmatic way of formulating: if a hypothesis that a certain condition did not change, cannot be rejected with the desired confidence, we say that the condition did not change.

The order in which hypotheses and relations are discussed below represent the logic followed when testing the three hypotheses. This logic is shown in the flow diagram of figure (A.1) in Appendix A, without yet specifying the individual areas or system relations. It is further discussed in Appendix A, section A.2.

3.3 Preprocessing of data

Before the actual hypotheses can be tested in the form of mathematical expressions an analysis of the data to be used in the test may be required. This 'preprocessing' may make use of techniques discussed in Appendix B, Section B.2. For example: data may have to be checked for sample biases (e.g. over/under sampling in particular seasons, systematic changes in sampling time with respect to the tidal phase, artificial trends due to changes in sampling techniques, biases towards weather conditions etc.) Also (especially for ARMA type of applications) time series need to be free of gaps. Hence, spatial aggregation of series may be required to arrive at composite time series representative for a certain area. Also temporal aggregation may be required to arrive at the shortest interval that is shared by series and which defines the effective resolution on which a series can be considered free of gaps and (equidistant in time). For each area, data set and method a data-analysis may be reuired. Particular techniques for this preprocessing are for example Harmonic Analysis (e.g. to identify deterministic low-frequency signals such as the 18.6-year nodal cycle or seasonal signals). Auto-correlation analysis to assess to what extent samples of a series are related in time, what memory time scales are, what a suitable temporal aggregation interval would be (de-correlation time scale) etc. Similarly, spatial aggregation can be carried out based on spatial covariance analysis: neighboring stations to be aggregated should have enough characteristics in common to be representative for a certain area.

Also, combining Remote Sensing and in situ data may help to generate composite data sets with higher spatial coverage to which certain methods can be applied. Methods to achieve this are not further elaborated upon here, but this an related issues are for example discussed in Vos & Schuttelaar (1995), Blondeau-Patissier et al, (2004), and Duin et al (2005a,b).
The details of the preprocessing required depend on detailed properties of the observational data and require more extensive data analysis than is feasible given the scope of the present project.

4 Reference conditions, Area A

4.1 *A priori* expectations

The majority of the suspended matter in the Dutch coastal zone is transported from source locations to the south of the Dutch territory. According to the system description, the major sources are the supply in the Dover Straits (where it arrives from eroded cliffs) and (occasionally) the Flemish Banks off the Belgian coast. If this supply would change (due to whatever cause) it is expected that the concentrations in the Dutch coastal zone will change accordingly. Depending on the nature and location of the change there may be a time lag involved up to several seasons if underway sediment buffering plays a role. More specifically, the concentration of SPM measured offshore of Zeeland can be considered as an upstream boundary condition, for the Haringvliet, Maasvlakte and Holland coast system.

The *a priori* expectation is that in this area no changes will occur in the key variables due to MV2. The changes that may occur should be ascribed to autonomous developments either affecting the Southern North Sea as a whole or acting locally. Examples are (climatic) changes in waves, winds, extension of Zeebrugge harbor moles, or different upstream SPM concentrations or residual transport velocities in the Dover Strait.

4.2 Key variables

Because a combined measurement of concentration and velocity is not available here the main key variable is SPM surface concentration from monitoring stations (including Belgian) and from remote sensing. In addition to SPM concentrations, it is worthwhile to apply the same hypotheses to SPM-related auxiliary variables that may explain observed changes in SPM data (if any). The most prominent are: signficant wave height and period (to determine near-bed wave orbital velocity[2]), Wind stress magnitude and direction, total mass of SPM dredged from port of Zeebrugge for maintenance. The main and auxiliary key variables for the reference area are listed in below. Figure 4-1 provides reference for the wave and wind stations within area A mentioned.

[2] *Wave orbital velocity that is a measure for stirring and mixing of sediments vertically, it can be calculated if wave height, period, wave length and local depth are known (e.g. using Soulsby, 1997)*

Table 4-1 Key variables to assess changes in the reference conditions of Area A. High and low frequency are relative to the dominant time scales in SPM signals which are the tidal period and the time scale of changing weather conditions. Time series that resolve the tides are considered high frequency. Time series with sample intervals of a few days or longer are considered low frequency.

Variable	Type	Source
SPM surface concentration	low-frequency time series, remote sensing imagery (low frequency)	Zeeland: MWTL data from DONAR, Belgian Coast: IDOD data, MERIS, MODIS, Orbview-2, IKONOS
depth-averaged current velocities off Zeeland and Belgium	maps (high-frequency storage) of 2DH hydrodynamic models	*Kustfijn* model in MATROOS data base
Sea Surface Salinity	low-frequency time series from monitoring	MWTL stations
signficant wave height & period, local depth, together as input to wave orbital velocity	high-frequency time series, bathymetric data	DONAR wave data from Europlatform and Light Vessel Goeree
wind stress magnitude & direction	high-frequency time series	HYDRA wind data from LV Goeree, Europlatform, Oosterschelde
dredged sediment mass for maintenance	time series (cumulative annual data)	various Belgian ports, mostly Zeebrugge, various dump sites

Figure 4-1 Wind and partly also wave observation stations in vicinity of Area A (source KNMI, HYDRA)

4.3 Specific hypotheses and test methods

Hypothesis I *"No change in SPM-related reference conditions"* can be detailed further:

a) no change in spatially aggregated, temporal mean conditions,
b) no change in the (spatially aggregated) temporal variability
c) no change in temporally averaged, spatial structure

These hypotheses are defined to test if the conditions related to SPM are significantly different after MV2. If for example differences in SPM concentrations and wave conditions are found, a next step may be to assess the consistency of a presumed relation between these two aspects. This is discussed in section 7.1 as it relates to the level III of the general hypotheses.

Below, examples are given of tests of the various sub-hypotheses (a to c) of hypothesis I. These can be elaborated further for the other key variables and other statistics (median etc.) and measures for temporal variability and spatial structure. Please note that various methods for testing temporal and spatial characteristics are further described in Appendix B.

4.3.1 Spatially aggregated, temporal mean

<u>Main key variable</u>: SPM surface concentration in area A.
After analysis of spatial correlations (see preprocessing) various physically sensible spatial aggregations may be feasible: e.g. aggregate all data of the different stations within the area, only the data at a certain distance from the coast, or a weighted average representative for the center of gravity of a certain transect.
The mean can be either the temporal mean over the total series, or seasonal means. Autocorrelation analysis may be used to determine a weighted mean (minimum variance estimator).
<u>Method</u>: Apply a two-sided test to the hypothesis that the mean of the SPM concentration (i.e. according to the mean of choice) after MV2 is not significantly different from the mean before. The mean can be a multi-year mean over entire years or a mean of the winter seasons or even multi-year means aggregated by month.

<u>Auxiliary key variable</u>: Wave orbital velocity, derived from significant wave height and peak period measured at one or more representative offshore stations (details relate to considerations of preprocessing illustrated above).
<u>Method</u>: similar to concentration, test hypothesis with respect to mean orbital velocity after MV2. Changes may be related to changes in SPM.

<u>Auxiliary key variable</u>: Wind stress derived from one or more representative stations.
<u>Method</u>: test mean direction and magnitude of wind stress

<u>Auxiliary key variable</u>: Total dumped mass of dredged material from port of Zeebrugge
Mostly annual mean data are available.
<u>Method</u>: test multi-year mean

4.3.2 Spatially aggregated temporal variability

Like the temporal mean described above, also a measure for the temporal behaviour (e.g. the typical range) of the concentration and SPM-related environmental conditions in the area can be derived.

Main variable: SPM surface concentration in area A
Determine quantiles (e.g. 5% and 95%) of SPM concentration to one or more of the spatial aggregations discussed under 4.3.1 over one or more of the suitable temporal periods.
Method: Apply a two-sided test to the hypothesis that the quantiles of concentration after MV2 are not significantly different from before MV2.

Auxiliary variable: Representative wave orbital velocity measured at one or more representative offshore stations.
Method: similar to c, test hypothesis with respect to quantiles after MV2

Auxiliary variable: Wind stress. For temporal behaviour a wind-stress rose can be analysed, giving more detailed information about statistics of the wind stress per sector of the rose than just the vectorial mean of the stress
Method: test whether changes in the wind-stress rose statistics are significantly different

4.3.3 Temporally averaged spatial structure

Even if the mean and measures for variability would not change, it is still possible that spatial distributions change within areas of aggregation. Therefore, it may be useful to test the spatial structure as well. For SPM concentration in general there is a clear cross-shore gradient (in time-average sense) with highest concentrations near the coast.

Main variable: SPM surface concentration $c(y,t)$ at specific along-shore locations x in area A
Key parameters: Parameters such as cross-shore gradient, position of center of gravity, etc of SPM surface concentration $c(y,t)$ in area A

Method: A statistical model can be formulated to describe the spatial structure in term of the key parameters. This model is identified on the basis of pre-MV2 (t_0) data. Uncertainties in the model and observations are represented by a spatial random noise. For the cross-shore (y) structure this can be formulated as follows:

$$c(y) = f(y \mid \Theta) + V_y \tag{4.1}$$

From the model a prediction is available plus confidence intervals. These can be used to verify whether any post-MV2 (t_1) observation on a particular location is likely or not, given the confidence interval. If any significant change in spatial patterns would occur, this would follow from significant, rejection of the model during t_1. The details of the procedure out outlined further in the appendix (B.4.2)

5 Conditions Area C (Holland coast)

5.1 A priori expectations

The a priori expectation is that conditions off the Holland coast north of MV2 may change notably due to the presence of the MV2. The more offshore input of the riverine water, the more westward transport of Haringvliet water and local hydrodynamic changes may lead to a different river plume (different SST and SSS distribution) and hence different spatial distribution of SPM. The general expectation is elevated concentrations offshore and reduced concentrations nearshore. This change may also be reflected in amount of dredging required to maintain the navigation channels towards the port of IJmuiden, and in the concentrations near the entrance of the port of IJmuiden (ADCP echoes). It is expected also that the absolute magnitude of the change will decrease further to the north. On the other hand, it is presumed a priori that wind and wave conditions will not change significantly in area C.

Also in this area there is large spatial and temporal variability in concentration. Concentration signals may propagate through the area with considerable time lag (months at least). Because of the extent of area C and the possible northward decrease of the signals of change, it may be worthwhile to apply the methods to sub-areas or individual transects within area C.

5.2 Key variables

Also here SPM flux across a transect cannot be derived from measurements. The main variable is SPM surface concentration from monitoring stations, from remote sensing, and potentially from ADCP at the IJmond. The ADCP also provides current velocities as does the operational model. These can also be subjected to testing.
Like for the reference area A, it is recommended to apply the same hypotheses to auxiliary variables to assess whether other simultaneous changes have occurred. The most relevant are: wave height and period, wind stress magnitude and direction, total mass of SPM dredged from port of IJmuiden for maintenance, sea surface salinity SSS, sea surface temperature SST, and discharges and possibly SPM loads from the Haringvliet, Nieuwe Waterweg and Noordzeekanaal (IJmuiden).
Table 5-1 lists all key main and auxiliary key variables for the Holland coast, whereas Figure 5-1 shows the wind stations for reference.

For all variables the specific sub-hypotheses and procedure is analogous to Area A as discussed in section 4.3.

Table 5-1 Key variables to assess changes in the conditions of Area C (Holland coast). The order reflects priority. For further comments see caption of Table 4-1.

Variable	Type	Locations
SPM concentration	low-frequency time series, remote sensing imagery (low frequency), high-frequency Smartbuoy time series	all MWTL stations from Noordwijk to Callantsoog and Remote Sensing by MERIS, MODIS, Orbview-2, IKONOS. Smartbuoy SPM data from the RIKZ/CEFAS project.
Depth averaged current velocities	high-frequency maps from 2DH hydrodynamic models (*Kustfijn & Zeedelta*)	entire coastal area
ADCP echo intensities and current velocities	high-frequency time series	IJmuiden IJmond
Signficant wave height and period, local depth	high-frequency time series, bathymetric data	Noordwijk, IJmuiden IJmond, IJmuiden, IJgeul (IJ5), IJmuiden Munitiestortplaats, Platform K13a
Wind stress magnitude & direction	high-frequency time series	IJmuiden, Noordwijk, Platform K13a
Sea Surface Salinity (SSS)	time series from monitoring	MWTL stations
Sea Surface Temperature (SST)	time series and remote sensing imagery	MWTL stations and remote sensing of coastal area (AVHRR)
dredge mass for maintenance port of Rotterdam and IJmuiden	time series (IJmuiden annual data, Rotterdam weekly data)	Taken from Ports of Rotterdam and IJmuiden, disposed at dedicated sites.
Discharge and SPM concentration Haringvliet & Nieuwe Waterweg, IJmuiden	low-frequency time series	Haringvliet sluices, Maassluis, Hoek van Holland, Brienenoord, Puttershoek. IJmuiden

Figure 5-1 Wind observation stations for Area C (source KNMI, HYDRA)

6 Conditions Area D (western Wadden Sea)

6.1 System relations, a priori expectations

Concentrations of SPM in the Wadden Sea may change due to different fluxes of SPM at the inflow boundaries. The fluxes in turn may change due to changing concentrations and or changing transport rates. The numerical model results by Van Kessel et al, (2006) suggest a decrease of annual mean concentration of a few percent (ranging from about 2 to about 7.5%) decrease in the annual mean.
The southernmost tidal inlet of the western Wadden Sea (Marsdiep) plays an important role in the transfer of SPM signals from the North Sea to the Wadden Sea. However, the SPM balance of the Wadden Sea not only depends on the flux through this particular inlet. For example a relatively low net SPM import through Marsdiep may imply that relatively more SPM is delivered to area D from other sources. These may be either the other inlets of which the Vlie inlet is the largest and of which the residual volume discharge tends to anti-correlate with the Marsdiep, or fluxes from Lake IJssel, or (not unimportantly) the local sea bed in the Wadden Sea.

6.2 Key variables

Again one main variable is SPM surface concentration from in situ monitoring within the Wadden Sea. However, for this area also the volume and sediment flux through Marsdiep can be derived from the ferry-mounted ADCP. Remote sensing is unreliable in the Wadden Sea. Auxiliary variables are wind data on stations surrounding the Wadden Sea, salinity data of the Marsdiep and Wadden Sea, and discharge through the Afsluitdijk sluices. Wave data are not available. The main and auxiliary variables are listed in Table 6-1 below. Figure 6-1 shows the wind stations of area D.

Table 6-1 Key variables to assess changes in the conditions of Area D (western Wadden Sea). For further comments see caption of Teble 4-1.

Variable	Type	Location
SPM concentration	low-frequency time series	MWTL stations in western Wadden Sea, NIOZ jetty observations Marsdiep
SPM flux through Marsdiep	ferrybox data	Marsdiep
volume flux of water through Marsdiep	ferrybox data, high-frequency time series time series	Marsdiep
wind stress magnitude & direction	high-frequency time series	Texelhors, De Kooy, Vlieland, Hoorn, Lauwersoog.
Aflsuitdijk discharge	moderately low-frequency time series	Sluices Kornwerderzand and Den Oever
Sea Surface Salinity	time series	Marsdiep and Wadden Sea

Figure 6-1 Wind observation stations in vicinity of Area D (source KNMI, HYDRA)

6.3 Specific hypotheses and test methods

The hypothesis *"No change in SPM-related conditions"* can be detailed further:

a) no change in spatially aggregated, temporal mean,
b) no change in a measures for the spatially aggregated, temporal variability

For the main variable the procedure is analogous to the discussion for Area A, sub (a) and (b). Hypotheses concerning change in wave and wind conditions may be tested in similar way. The interest is not primarily in spatial structure of (changes in) SPM data inside the Wadden Sea, although changes in the spatial structure may yield additional information on the nature of the change (e.g. indicate possible sources). It should be noted that there are no monitoring series of wave data inside the Wadden Sea. A parametric relation may be constructed to relate wind conditions at the Wadden Islands to representative wave conditions, and through that to SPM concentrations.

Finally, relations between Marsdiep data and SPM inside the Wadden Sea and between sluice discharge and SPM may be useful. These are subject of hypotheses level III which is discussed in the next chapter.

7 Hypothesis III: No change in system functions

System functions are statistical expressions that relate to the functioning of the coastal SPM transport system. They describe the spatial and temporal relation between SPM data observed at different sites or at different times or they relate various external conditions (forcing conditions) to observed SPM data. Transfer of SPM signals in fact is related to the residual flux of SPM from south to north along the Dutch coast. Since the flux itself is very hard to measure, because of lacking current velocity data and information on the vertical structure of the concentrations fields, testing relations across space and time is an alternative way to obtain information on changes in the system related to fluxes of SPM.

The proposal here is to formulate these functions using ARMAX models (see sect. B.5.2) and use these to test if significant changes in the functioning of the system have occurred. This method imposes additional requirements on the data (see sect. 3.3). The input and output data and additional input data can be derived from limited spatial areas (particular transects) or from a larger aggregates, depending on results of the preprocessing and spatial correlations found. Also, the (presently unknown) future range of data the model will be applied to should not be too much different from the present range. An ARMA model is trained on the present data and in such sense a linear approximation valid for the range of the present data.

The general idea is to formulate these system functions and carry out the tests only if found appropriate after testing the general conditions (hypotheses I and II). Also, as outlined in section B.5.1, more elementary techniques are required first to evaluate the nature of change. Elementary analysis also helps to choose which terms to include in a system function.

The proposed priority is to first establish relations between main variables (concentration) across areas (so excluding additional forcing terms). Only if necessary, auxiliary (forcing) variables such as wave conditions, winds, currents, river discharges should be incorporated. The relations are discussed following the geographical order from area A to D.

7.1 Relations within Area A

If changes are observed in the reference conditions in Area A, it may be worthwhile to examine what the cause of these changes has been. If the cause turns out to be very localized it may be easier to separate influences due to this change from any possible MV2 effect further downstream. If, on the other hand, changes appear to have a more global nature they may contaminate the conditions downstream. In that case relations between area A and C need to be investigated (Sec. 7.2).

7.1.1 Spatial and temporal relation of SPM

Possible observed changes in spatial structure of the reference conditions can be analysed by formulating relations between conditions at a certain location or transect to the conditions further south of it. In this way, it can be seen if and, if so, how strongly a local change in the south penetrates towards the north (i.e. to what extent a model turns out to have significant predictive power).

Statistical model relations can be established between time series of the Zeeland data as function of data further to the south. The model relations are developed under t_0 conditions and tested under t_1 conditions. From the model's predictive performance it can then be assessed whether the system functions differ significantly or not.

7.1.2 Relation forcing-SPM

The local SPM conditions in Area A before MV2 can be related to forcing conditions before MV2 by means of a regressive model as well. For t_1, the new forcing conditions can be fed into the model and the predicted SPM conditions can be compared to the actually observed. Given the confidence intervals of the model it can be assessed whether the modeled relation is preserved in statistical sense and, if so, it yields an explanation for observed changes. If not, the cause of changes in SPM conditions may be outside the scope of the relations investigated. The regressive model can be supplied with one or more of the key variables of Table 4.2 and its skills need to be established using pre-MV2 data (also training of the model).

7.2 Relations within and with Area C

Concentrations of area C can be related to concentrations in area A. Presumably the most fruitful approach is to consider spatial aggregates of SPM concentrations in both areas or well-covered stations on transects. One possible change mentioned in Section 2 is an increase in time lag between A and C due to increased residence time in Haringvliet mouth. This time lag could be investigated using cross-correlation analysis of time series north and south of the Haringvliet and MV2. Testing the significance of a change in correlation time scale may be difficult though. An alternative is to develop an ARMAX model that relates concentrations with a certain time lag. Of that model the predictions during t_1 can be assessed with significance. Again, the model is trained on pre-MV2 conditions and tested after MV2.

Because responses due to MV2 may have different magnitude (or even sign) within Area C, spatial nuance may be required. For example a change may still be notable directly north of the MV2 but the signal may become weaker further north. By testing the relations for consecutive transects it can be shown where the signal of changes (if any) loses significance.

Again the models may also incorporate other variables. For the entire area C or for sub domains the relation between SPM data and other (forcing) factors can be tested. The following forcing conditions may be taken into account:

- wave conditions in area A and C
- wind conditions in areas A and C;
- SSS & SST in area C
- Currents of area C

Because area B is a source region of disturbances to signals passing from A to C certain elements of area B may be added to the transfer functions as well. Possible sensible additions are:

- wind and wave conditions in area B;
- discharges Haringvliet and Nieuwe Waterweg,
- amounts and locations of sediment disposed due to dredging of port of Rotterdam (dredging requirements of the port of Rotterdam are expected to change due to MV2)

An example is an ARMAX model that yields SPM concentrations in a certain region within area C as function of not only the concentrations in area A but also the river discharge through Haringvliet and Nieuwe Waterweg (as individual variables). If the predictive skill of a model that incorporates these river discharges is preserved after MV2, an explanation for possible observed changes north of MV2 may be given that excludes MV2 itself.

7.3 Relations within and with Area D

The relations between SPM conditions in the Holland coast (area C) and Wadden Sea (area D) can be formulated again firstly in terms of concentrations, and only secondly also including additional information. Various relations can be tested for various input regions within area C. In particular, it is advised to test transfer functions from the Egmond and/or Callantsoog transects or larger spatial domains in the northern Holland coast to spatially aggregated SPM concentrations in the western Wadden Sea. Additional input may in particular be the Marsdiep ferrybox data (volume fluxes and (measures for) SPM fluxes). Alternative models may also incorporate wave and wind conditions in both the Wadden Sea and north of area C.

The most prominent local forcing terms are

- sluice discharge through the Aflsuitdijk,
- direction and magnitude of wind stress,

Again, if a skillful model only including local forcing can be defined for t_0, it can be used to test whether t_1 changes in SPM in the western Wadden Sea are consistent with possible simultaneous changes in forcing conditions. Comparing the skill of such a model to those that also incorporate SPM signals that may be affected by MV2 may give an indication if any changes in the Wadden Sea are due to local causes or related MV2-induced changes off the Holland coast. To phrase it differently: the least one can conclude is that, if any observed change can be predicted within the confidence bandwidth of a model only relying on local forcing, any additional effect of MV2 is of secondary relevance.

In principle it is possible to relate concentrations in area D to concentrations in area A, similarly to section 7.2. However, as this spans a long distance with many intermediate links and nonlinearities that are neglected, it is not expected that such models will have much predictive power.

8 Example: tests the mean of some *in situ* SPM time series.

8.1 Introduction

The assessment of changes in the mean of SPM-concentrations north of MV2 is one of the statistical tests proposed in Chapter 4 and further outlined in Appendix B. In Chapter 4 this issue was considered mainly from a physical viewpoint (cause effect relations, hypotheses and key variables). In this chapter results will be shown of a few preliminary applications to demonstrate the practical significance and suitability of the method.

In this chapter examples of time series of SPM concentrations as observed at two different distances offshore (2 and 20 km) on two transects off the Holland coast have been considered: Noordwijk and Callantsoog. For the Noordwijk transect not only MWTL[3] survey data have been considered but also data obtained from OBS devices that were mounted on a Smartbuoy operated by CEFAS and RIKZ. (Hence referred to as 'CEFAS' or 'Smartbuoy data' for brevity.). Smartbuoy data of the Noordwijk 02 and Noordwijk 10 sites have been considered. We refer to Blaas et al., 2006 for further description of these data sets and the location of the stations. In this section basic properties of mainly the two Noordwijk SPM-time series are presented. This is done by means of elementary statistics and some results of standard time series analysis procedures. The two stations serve as an example of elementary analysis required for all series one wishes to consider and advise on optimization of continuation of such series during future monitoring.

In the following sections first the characteristics of the series will be discussed, mostly focused on the Noordwijk series to aid the discussion of statistics later. Then, the hypothesis of no change in the long-term mean is tested on the Noordwijk MWTL data, by assuming the introduction of a fictive possible effect halfway the series. Finally, the requirements of future (t_1) measurements are explored. Here we assumed that the presently investigated series will be continued and ask the questions for how long with what sampling frequency one needs to sample in order to detect certain changes in the long-term mean between the baseline (t_0) and future (t_1) series.

[3] *MWTL: Monitoring van de Waterstaatkundige Toestand des Lands*

8.2 Properties of Noordwijk 02 and 20 SPM-time series

8.2.1 Temporal evolution

At the Noordwijk transect surface concentrations of SPM have been measured at 2 and 20 *km* offshore during MWTL monitoring. The time period covered by both series ranges from May 1975 to December 2005. For both series it must be noted that the observation times are not equidistant, and the time intervals between two successive measurements vary from a few days to more than a month, or even larger.

A plot of these two observed time series can be found in Figure 8-1. The red dots "•" represent the actual measurements which are interconnected by blue line segments. The blue curves then provide a visual impression of the temporal variability in the SPM-series. It must be emphasized, however, that this curve must be interpreted with care, and should not simply be considered as a reliable temporal interpolation of the red measurement points. In fact, as will be discussed later in this chapter, it was found that a vast majority of the time intervals between successive measurements is larger (or even much larger) than the auto-correlation time of the two SPM-processes. Therefore the temporal variability of the true SPM concentration between successive measurement points can be significantly larger than suggested by the (blue) linear interpolation shown in Figure 8-1. This is demonstrated on the basis of a second data set with a much higher temporal sampling density which happened to be available for Noordwijk-02. This set consists of near-surface SPM concentrations measured with the CEFAS Smartbuoy (Hartog & Van de Kreeke, 2003) which for a period of about 100 days in September-December 2001 the data are available in the form of hourly samples. These CEFAS Noordwijk-02 data are plotted in blue in Figure 8-2, together with the MWTL SPM-samples as shown in Figure 8-1. The MWTL samples are again indicated by red dots. From Figure 8-2 it is obvious that the temporal variability in the SPM series is much higher than can be resolved from the sampling rates of the data plotted in Figure 8-1.
The CEFAS data thus tend to be of a much higher quality. For a future statistical analysis of MV2-effects they may be of limited value, however. The reason is that CEFAS for Noordwijk 02, cover a too short time periods to obtain statistically meaningful measures for a proper description of the pre- MV2 conditions. Therefore the present examples of statistical tests will be based on the data of rather than the CEFAS set of Figure 8-2.

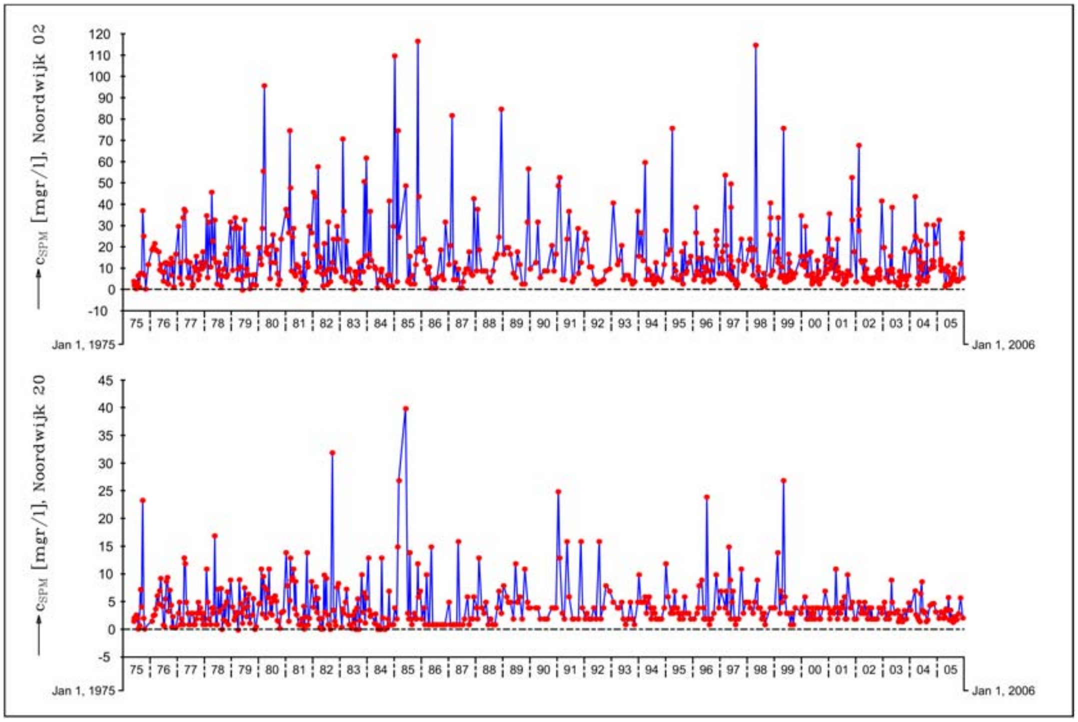

Figure 8-1 Plot of the MWTL SPM-time series measured at Noordwijk-02 (upper panel) and Noordwijk-20 (lower panel). The measured samples are denoted by the symbol "•" while the blue curve represents a linear interpolation of these samples.

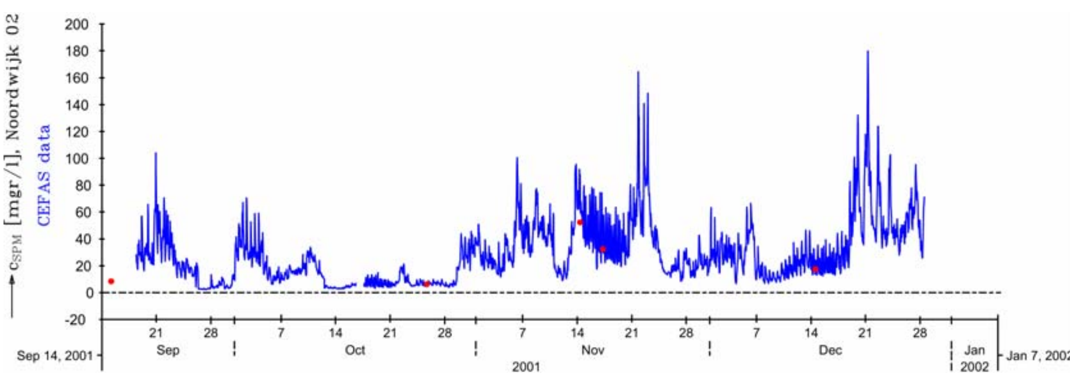

Figure 8-2 Plot of the CEFAS SPM-time series measured at Noordwijk-02 in the last 4 months of 2001 (blue solid curve). The symbols '•" denote the Noordwijk-02 samples of the MWTL SPM data set.

8.2.2 Marginal distribution

Basic statistical properties of the observed SPM concentrations can be found in quantitative form in Table 8-1. The quantities listed in this table characterise the marginal distribution of the measurements $\{c_{02}(t_k)\}_{k=1}^{K}$ and $\{c_{20}(s_\ell)\}_{\ell=1}^{L}$ shown in Figure 8-3. An (empirical) estimate of these two marginal distributions (histograms, normalised to unit area below the curves to represent a probability density function) can be found in Figures 8.2.1*ab*. In these figures, the black vertical lines indicate the position of the 2.5% and 97.5% quantiles, while the red vertical lines marked by the symbol "*" represent the position of the mean. Clearly both distributions are highly skew, as is also indicated by the skewness coefficient listed in Table 8-1. The table and figures also indicate that on the average the observations of $c_{20}(\cdot)$ are about 4 times smaller than those of $c_{02}(\cdot)$.

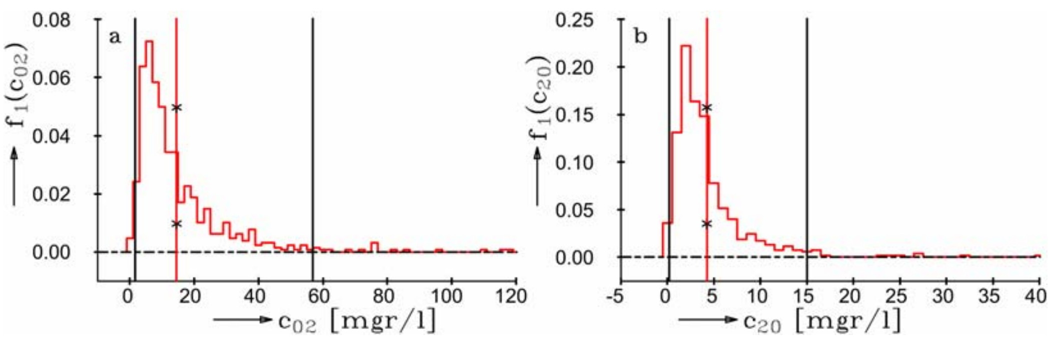

Figure 8-3 Marginal (probability density) distributions of the observed $\{c_{02}(t_k)\}_{k=1}^{K}$ (Noordwijk 02, left) and $\{c_{20}(s_\ell)\}_{\ell=1}^{L}$ (Noordwijk 20, right) data.

Table 8-1 Elementary statistics of two measured Noordwijk SPM time series.

Statistic	*Time Series*	
	$c_{02}(\cdot)$	$c_{20}(\cdot)$
N^o. samples	642	526
Mean [*mg/l*]	14.56	4.27
Spread [*mg/l*]	15.11	4.25
Skewness marginal distribution	2.96	3.38
2.5% quantile [*mg/l*]	1.72	0.20
97.5% quantile [*mg/l*]	56.93	15.00
Upper extreme [*mg/l*]	117.0	40.0
Mean sampling interval [*days*]	17.40	21.25

8.2.3 Temporal properties

Auto-correlation and cross-correlation functions were computed of the $c_{02}(\cdot)$ and $c_{20}(\cdot)$ series to verify time scales and temporal memory in the processes. Unfortunately, in the present case the samples of the time $c_{02}(\cdot)$ and $c_{20}(\cdot)$ are not on an equidistant temporal grid and therefore the standard recipe for the computation of the correlation function must be slightly adjusted. See the intermezzo below. It can be skipped by the reader not interested in these technical details.

Intermezzo: Correlation function for time series not on equidistant time grids.

In case of time series on different and/or non-equidistant time grids the standard recipe for the (auto/cross)correlation function must be adjusted. This can be done by the following practical approach. As usual the correlation function is computed for time shifts τ_n on an equidistant grid $\tau_n := n \cdot \Delta\tau,\ n \in \mathbb{Z}$. For the time lag τ_n (and temporal resolution $\Delta\tau$) the cross-correlation function $\rho_n := \rho(\tau_n)$ for the two time series $\{\, c_{02}(t_k)\,\}_{k=1}^{K}$ and $\{\, c_{20}(s_\ell)\,\}_{\ell=1}^{L}$ is now defined as the standard correlation coefficient of all the paired samples $(\, c_{02}(t_k),\, c_{20}(s_\ell)\,)$ that satisfy that $n-\frac{1}{2} \le \dfrac{s_\ell - t_k}{\Delta\tau} < n+\frac{1}{2}$. In words this means that for the time shift τ_n the correlation $\rho(\tau_n)$ is based on the samples whose time lag $s_\ell - t_k$ is in the *n*-th bin. This *n*-th bin is $[\tau_n - \frac{1}{2}\cdot\Delta\tau\ ,\ \tau_n + \frac{1}{2}\cdot\Delta\tau)$. This recipe is consistent with the standard formulation of the auto-correlation function in the sense that in case of two time series on the same equidistant time grid (i.e. $t_k = t_0 + k\cdot\Delta t$, and $s_\ell = t_0 + \ell\cdot\Delta t$, and $\Delta\tau = \Delta t$) the usual expression will be retrieved.

A proper choice must be made yet for the temporal resolution $\Delta\tau$. A large value of $\Delta\tau$ has the advantage of many hits (i.e. many (t_k, s_ℓ)-combinations within each bin of the correlation function), but is at the cost of (too) large smoothing, and thus loss of accuracy. A small $\Delta\tau$ will lead to (too) few hits in many bins, and thus noisy and inaccurate estimates for the correlation coefficient.

In practice the mean interval $\langle \Delta t_k \rangle$ ($\Delta t_k := t_k - t_{k-1}$) between adjacent samples in the series may be a good choice for $\Delta\tau$, or alternatively the modus or 50%-quantile of all the $\{\Delta t_k\}_{k=1}^{K}$.

The auto/cross-correlation functions of the $c_{02}(\cdot)$ and $c_{20}(\cdot)$ were computed with a resolution $\Delta\tau$ =15.0 days. This resolution is slightly less than the mean sampling intervals of the two series, see Table 8-1). The so found estimates for the auto-correlation function (ACF) of $c_{02}(\cdot)$ and $c_{20}(\cdot)$ are shown in Figure 8-4 and Figure 8-5 respectively, while the cross-correlation function (CCF) of $c_{02}(\cdot)$ and $c_{20}(\cdot)$ can be found in Figure 8-7. In all these figures the red curves denote the estimate of the (auto/cross)correlation coefficient while the blue curves indicate the lower and upper limits of a 95% confidence interval for this correlation coefficient.

The ACF of $c_{02}(\cdot)$ (Figure 8-4) reveals a relatively strong periodic component with a period of one year. Such a period component tends to be less pronounced, or even absent in the ACF of the $c_{20}(\cdot)$ (Figure 8-5). Probably this is due to much larger (seasonal) effects of the River Rhine discharges and waves on $c_{02}(\cdot)$ series (closer to shore, shallower, and within the zone of silt transport ('Silt River') than on $c_{20}(\cdot)$ (more offshore, deeper, and most often beyond the Silt River).

For a more adequate assessment of seasonal effects in the series monthly means were computed. More precisely: all samples of $c_{02}(\cdot)$ were selected that were measured in January 1975, or January 1976, or January 1977, etc., until January 2005, and from the so found subset the average was computed. This recipe was repeated for the other months. Similarly this was then done for the $c_{20}(\cdot)$ series. The so found "time series" of monthly means are shown in Figure 8-6*a* for $c_{02}(\cdot)$, and in Figure 8-6*b* for the $c_{20}(\cdot)$ series. These figures then confirm a clear seasonal component in $c_{02}(\cdot)$, and a weak or even absent seasonal variation in $c_{20}(\cdot)$

Apart from a seasonal component, the ACF of $c_{02}(\cdot)$ does not provide any indication for other "significant" long(er) term variations. For the $c_{20}(\cdot)$ series this absence of longer term variations tends to be even more pronounced. In fact, in the ACF of Figure 8-5 much weaker correlation is observed for time shifts larger than 15 days.

The cross-correlation function (CCF) of $c_{02}(\cdot)$ and $c_{20}(\cdot)$ (see Figure 8-7) suggests that for time shifts larger than 15 days there is neither a significant mutual correlation of these two series. For a zero shift there tends to be some dependency but with the present low sampling rates (with a mean sampling interval greater than 15 days) more accurate estimates are not feasible. The absence of significant mutual correlation of two stations 18 km apart on the same transect suggests that when spatially aggregating and/or constructing system relations attention should be paid to the decision which station to select. The strong cross-shore gradients reflect also cross-shore changes in system properties. Aggregating neighboring stations that are roughly at the same distance offshore is presumably more sensible.

The CEFAS data of Noordwijk-02 (with sampling interval $\Delta t = 1$ *hour*, apart from a gap of about 1 *day* in the series, see Figure 8-2) can conveniently be used, however, to verify the (existence, effects, and/or properties of) shorter term fluctuations. To obtain a first idea, the ACF of these series was computed as well, and the result is shown in Figure 8-8. In this case the auto-correlation structure is well resolved for time lags less than 15 days and now variations in the ACF can be observed not present in the one of Figure 8-4. It is beyond the present scope to speculate in further detail about the origin of these variations, and here we merely want to subtract the finding that memory of the shorter term variations (i.e. fluctuations of smaller time scales than seasonal periodicities) is of the order of 5 to 15 days.

This estimate will later be used in Section 8.4 where on the basis of pre MV2 data the amount of post MV2 data is computed that is required to identify significant changes in the mean.

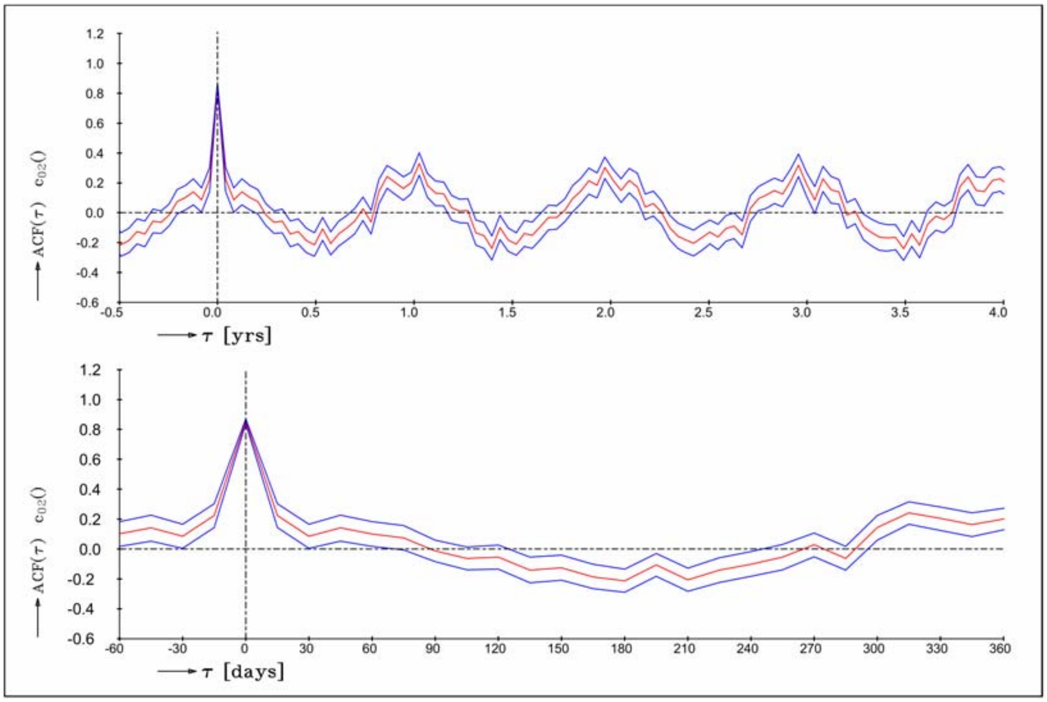

Figure 8-4 Auto-Correlation Function of the observed Noordwijk 02 SPM-time series of the MWTL monitoring. Lower panel is a zoom of the upper panel.

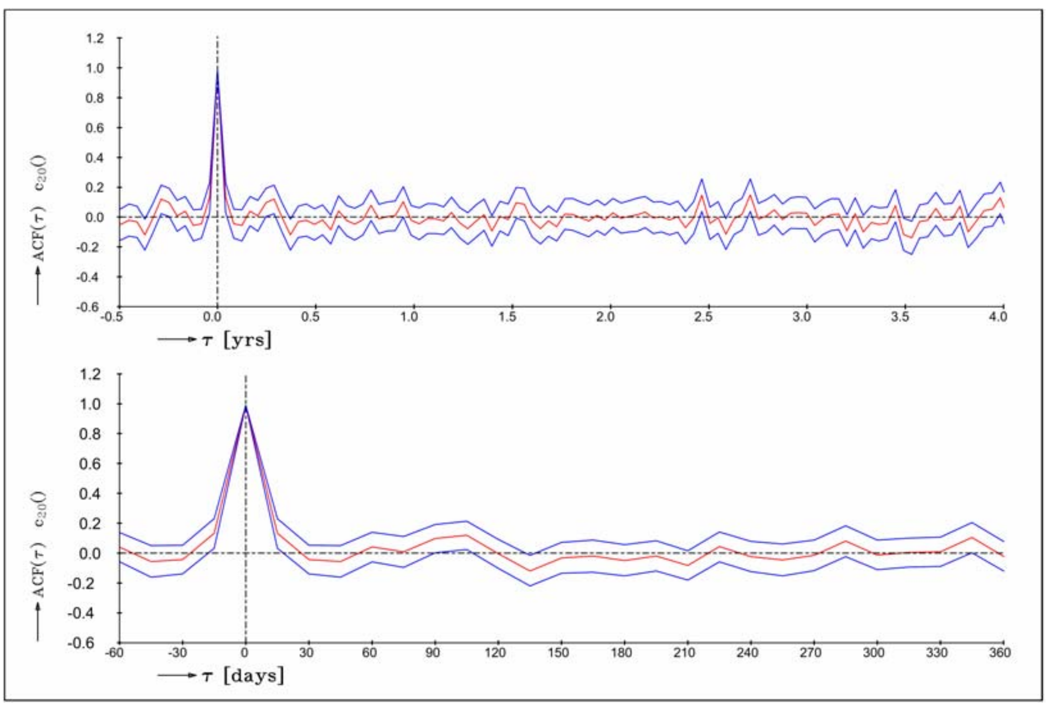

Figure 8-5 Auto-Correlation Function of the observed Noordwijk 20 SPM-time seriesof the MWTL monitoring. Lower panel is a zoom of the upper panel.

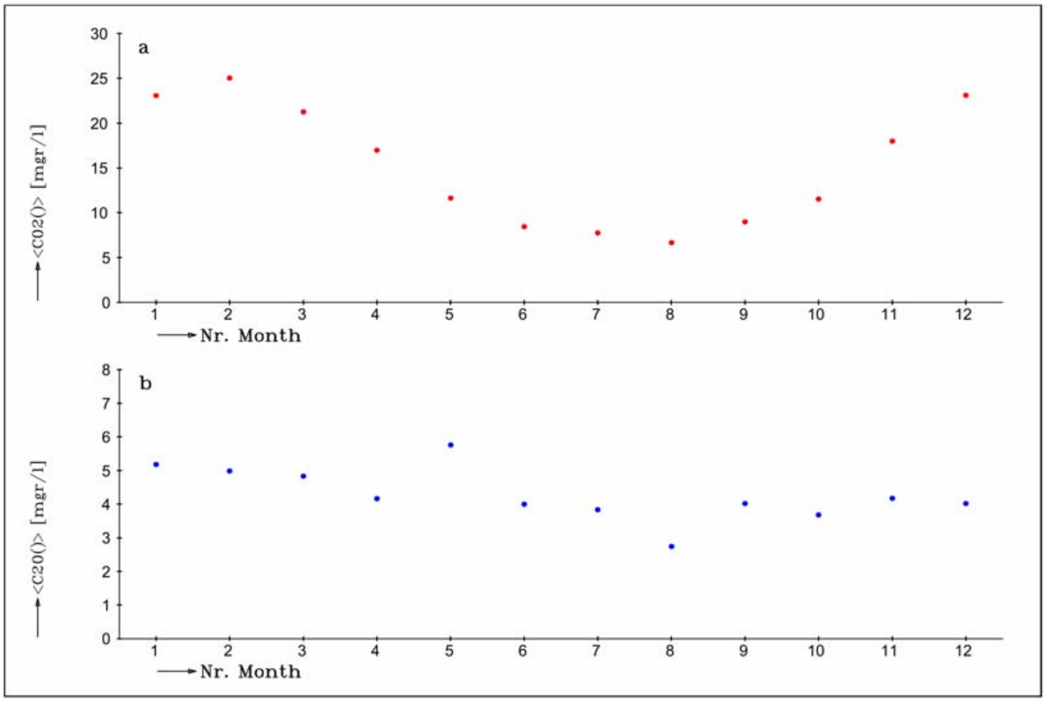

Figure 8-6 Monthly means of the Noordwijk 02 (upper panel) and Noordwijk 20 (lower panel) SPM-time series of the MWTL monitoring.

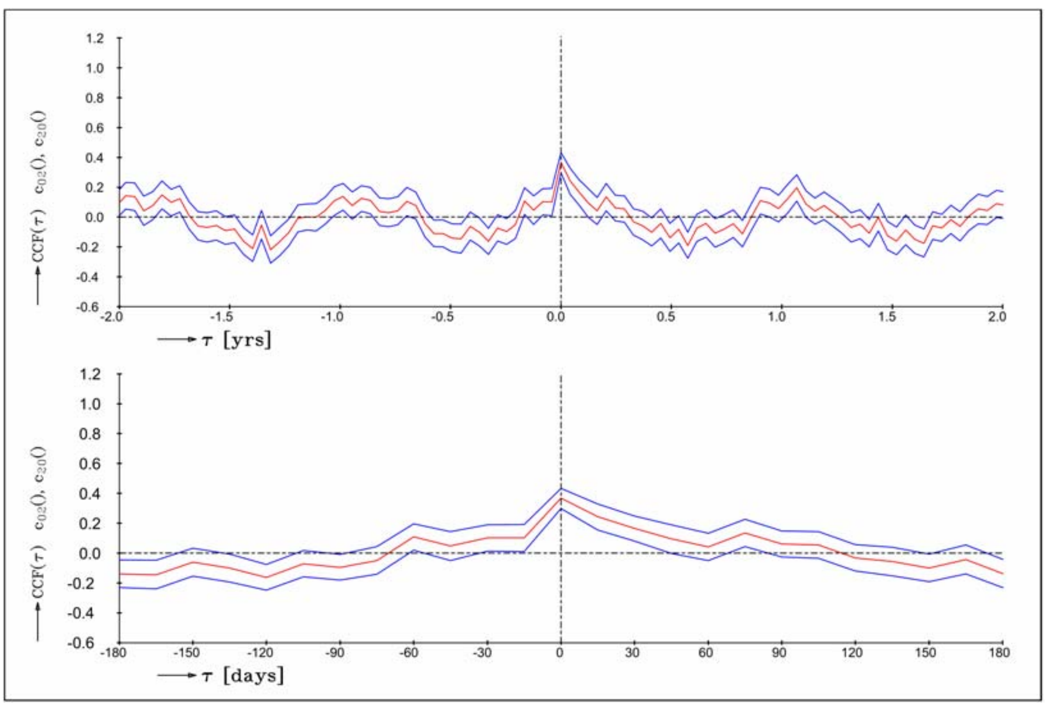

Figure 8-7 Cross-Correlation Function of the observed Noordwijk 02 (c_{02}) and Noordwijk 20 (c_{20}) time series of the MWTL monitoring. Lower panel is zoom of upper panel.

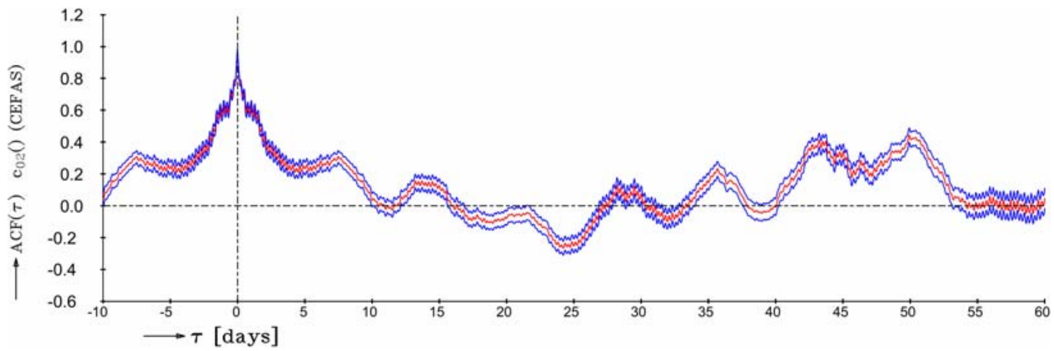

Figure 8-8 Auto-Correlation Function of the observed Noordwijk 02, CEFAS Smartbuoy time series.

8.3 Test current SPM time series Noordwijk 02 and 20

In this section the results of some statistical experiments are carried out dealing with the assessment of statistically significant changes in the mean of pre-event and post event SPM-measurements of de Noordwijk data. In this case the “event” is an imaginary MV2-extension that is supposed to have taken place at a certain moment in the currently available time series. Please note that in this and the subsequent sections the SPM time series have not been transformed (see Appendix B.2.4), despite the fact that Figure 8-3 shows that the distributions of the data is not symmetric. This is done to keep the interpretation of relative changes in the mean straightforward. It is expected that transformation of the data will influence the results only slightly (e.g. slightly different autocorrelations and spreads), but it does not affect the general methodology which is independent of transformation. Also, the two-tailed testing of the hypothesis (‘no changes in the mean’) would not be different as the distribution of the mean is normal for sufficiently many samples, as is the case here (central limit theorem).

In these experiments the Z-statistic will be applied as described in further detail in Appendix C, and formulated by Equation (C.1). The means $\overline{c}^{(-)}$ and $\overline{c}^{(+)}$, and spreads $\overline{\sigma}^{(-)}$ and $\overline{\sigma}^{(+)}$ are computed as described in Section C.2, using the Equations (C.8). In this way mutual dependencies in the measurements are explicitly taken into account.

The data representing the pre-event series $c^{(-)}$ and the post event series $c^{(+)}$ will be selected from the Noordwijk-02 and Noordwijk-20 SPM data sets that were analysed in the previous sections.

Because subsequent samples are not necessarily statistically independent, the correlation coefficient β of neighboring samples must be applied. As discussed in Appendix C2, this reduces the actual number of (mutually dependent) samples K of a series to an equivalent number $K_{Eff} = \frac{1-\beta}{1+\beta} \cdot K$ of effectively independent samples according to:

$$\beta := \exp\left(-\frac{\langle \Delta t \rangle}{\tau_{AC}}\right).$$

Here <Δt> is the mean time interval between successive samples of a pre-event series or a post event series. In this way the pre-event $<\Delta t^{(-)}>$ and post-event $<\Delta t^{(+)}>$ will in general be different, as will be the correlation coefficients $\beta^{(-)}$ and $\beta^{(+)}$. The way the correlation coefficient β depends on sampling interval Δt and auto-correlation time τ_{AC} is shown in Figure 8-9. Obviously, the exponential decrease of β for increasing Δt is stronger for smaller τ_{AC}. Hence accurate assessment of τ_{AC} is essential to optimize the sampling interval. For accurate assessment of τ_{AC}, high-frequency data (with respect to expected τ_{AC}) are required.

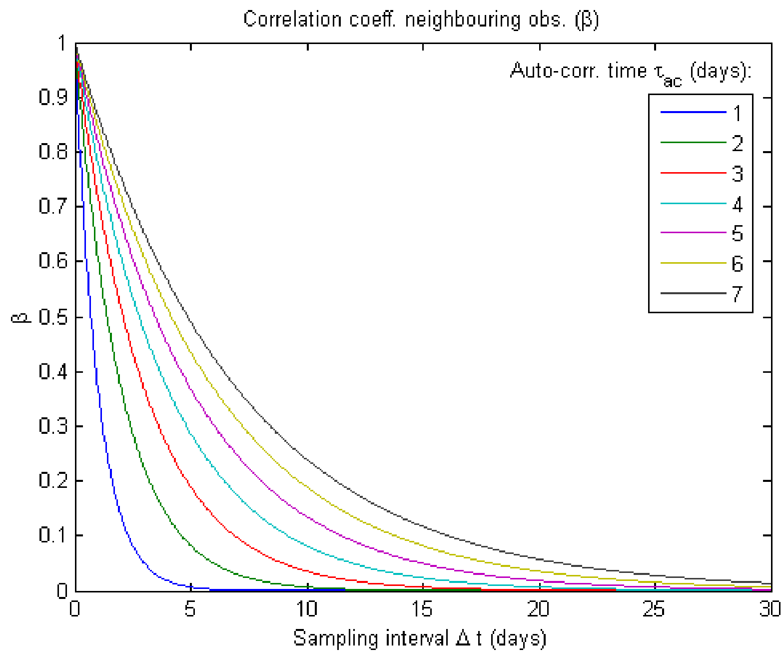

Figure 8-9 Correlation coefficient of neighbouring observations ('sample correlation coefficient', β) as function of mean sampling interval Δt and auto-correlation time τ_{AC}.

For the auto-correlation time τ_{AC} two variations are considered, τ_{AC}=7 days and τ_{AC} =15 days. This choice is based on the auto-correlation functions shown in Section 8.2. These correlation functions indicate that the "true" auto-correlation time is within the range bounded by the two values here selected. For ease we will assume that the pre- and post-event auto-correlation times are identical, and is also the same for the Noordwijk-02 and Noordwijk-20 series.

The set up of the experiments is that an event is assumed to have occurred at 01 January 1993 that may have affected the SPM-conditions at Noordwijk. Noordwijk SPM observations from before this date are considered as pre-event data $c^{(-)}$, while those after that date are treated as post-event data $c^{(+)}$. For the location of the data we can choose from Noordwijk-02 or Noordwijk-20, so that in total 4 combinations of pre- and post-event data can be constructed. In this selection of pre- and post-event data sets the "original" SPM measurements were used, without adding any noise, systematic changes, or other perturbations. In this way we are then actually testing whether or not the means from before and after 01 January 1993 are statistically consistent.

The results of this experiment for an assumed auto-correlation time of τ_{AC}=7 days are summarised in Table 8-2, while those for τ_{AC}=15 days can be found in Table 8-3. The columns with label "$c^{(+)}$" indicate whether Noordwijk-02 (c_{02}) or Noordwijk-20 (c_{20}) measurements (from be-ore 01 January 1993) were assigned to the pre-event data set. Similarly the columns with label "$c^{(+)}$" provide the origin of the post-event data set with measurements after 01 January 1993.

Table 8-2 Statistics (number of data points (K); effective number of data points when correcting for auto-correlation in the measurements (K_{Eff}), mean, and spread in the mean) for 4 variations of pre-event $c^{(-)}$ and post-event $c^{(+)}$ data sets for an autocorrelation time τ_{AC} of 7 days. The last columns provides the Z-statistic for testing of the difference of the means of the pre-event and post-event data sets.

Nr. Exp	Pre-event series $c^{(-)}$; τ_{AC} =07 days					Post-event series $c^{(+)}$; τ_{AC} =07 days					Z
	$c^{(-)}$	K	K_{Eff}	Mean	Spread	$c^{(+)}$	K	K_{Eff}	Mean	Spread	
1	c_{02}	312	281	16.39	1.02	c_{02}	330	254	12.83	0.80	-2.75
2	c_{02}	312	281	16.39	1.02	c_{20}	216	198	3.98	0.22	-11.9
3	c_{20}	310	279	4.47	0.29	c_{02}	330	254	12.83	0.80	9.80
4	c_{20}	310	279	4.47	0.29	c_{20}	216	198	3.98	0.22	-1.34

Table 8-3 As Table 8-2 but for an autocorrelation time τ_{AC} of 15 days.

Nr. Exp	Pre-event series $c^{(-)}$; τ_{AC} =15 days					Post-event series $c^{(+)}$; τ_{AC} =15 days					Z
	$c^{(-)}$	K	K_{Eff}	Mean	Spread	$c^{(+)}$	K	K_{Eff}	Mean	Spread	
1	c_{02}	312	186	16.39	1.25	c_{02}	330	147	12.83	1.05	-2.18
2	c_{02}	312	186	16.39	1.25	c_{20}	216	135	3.98	0.27	-9.71
3	c_{20}	310	186	4.47	0.36	c_{02}	330	147	12.83	1.05	7.51
4	c_{20}	310	186	4.47	0.36	c_{20}	216	135	3.98	0.27	-1.10

For a 95% significance level the critical values of Z are -1.96 and 1.96. From the tables it is then readily verified that (for both two variations of the auto-correlation time) the means of the Noordwijk-02 and Noordwijk-20 data are significantly different. This is as could be expected from the plots of the series, and the elementary statistical properties that were computed in Section 8.1.
The non-significant difference of the means of the data from before and after 01 January 1993 is neither a surprise, although Z-values closer to zero might have been expected. Most striking, however, is the significance (95%) of the difference in the means of the $c^{(-)}$ and $c^{(+)}$ subsets. It is at present not clear whether this is due to a (North Sea) system change, or essentially different (meteorological/hydrological) forcing before and after 1993 or whether

a change in the measurement protocol in the early ninety's plays a role. Therefore it is recommended to assess the forcing conditions as well as effects of different measurement protocols in further detail, and develop appropriate data-correction procedures. This is an important issue for further investigation, and is critical when in the future pre and post Maasvlakte 2 data are compared and statistically tested for differences. Also, additional suggestions for further analysis of these data is to for example explore the characteristics of differences of series of neighbouring stations, which gives information on the temporal behaviour of along-shore and cross-shore gradients.

8.4 Requirements for continuation of series (t_1 monitoring)

8.4.1 General background

In Section 8.3 the significance of different means before and after an (imaginary) event was quantitatively verified by means of applications to Noordwijk 02 and 20 measurements. In this section this topic is revisited, but now in an inverse way. In fact, we now deal with the question how many t_1 measurements are required to identify a statistically significant change in the mean of an SPM-series at a certain location.

First of all it must be realised that for a given confidence level (with the associated significance level α, and critical value critical value z_{Cr}^{α} for the Z-statistic) there is an asymptotical minimal change in the mean that can be detected as α-significant on the basis of future measurements. This minimum is approached in case of infinitely many future measurements the new mean $\overline{c}^{(+)}$, which leads to zero spread in the mean, i.e. $\overline{\sigma}^{(+)} = 0$. To find a significant change in the mean we must have

$$|Z| > z_{Cr}^{\alpha} \tag{8.4.1}$$

From Section C.1 it is recalled that the Z-statistic is defined as

$$Z = \frac{\overline{c}^{(+)} - \overline{c}^{(-)}}{\sqrt{\left(\overline{\sigma}^{(+)}\right)^2 + \left(\overline{\sigma}^{(-)}\right)^2}} \tag{8.4.2}$$

Combination of Equations 8.4.1 and 8.4.2, with $\overline{\sigma}^{(+)} = 0$ leads to the restriction that the difference $\Delta\overline{c} := \overline{c}^{(+)} - \overline{c}^{(-)}$ must satisfy:

$$\left| \Delta\overline{c} \right| \; > \; z_{Cr}^{\alpha} \cdot \overline{\sigma}^{(-)} \tag{8.4.3}$$

to be identifiable with the prescribed significance.

From Equation 8.4.3 it can thus be concluded that the minimal detectable change in the mean is $Min\left[\left|\Delta\overline{c}\right|\right] = z_{Cr}^{\alpha} \cdot \overline{\sigma}^{(-)}$. It must be noted that this minimal change depends (amongst others) on the chosen significance. Later in this section estimates of this $Min\left[\left|\Delta\overline{c}\right|\right]$ can be found for SPM series collected at stations on the Noordwijk transect and on the more northerly Callantsoog transect.

We now deal with the problem how many t_1 measurements are required (and the associated length of the measurement period) to identify a *prescribed change* $\left|\Delta\overline{c}\right|$ in the mean, provided that this change is larger than $Min\left[\left|\Delta\overline{c}\right|\right]$ and thus satisfies Equation 8.4.3. From Equation 8.4.2 it is readily verified that the amount of (future) measurements should be large enough to ensure that the spread $\overline{\sigma}^{(+)}$ in the estimate of $\overline{c}^{(+)}$ satisfies:

$$\overline{\sigma}^{(+)} \leq \sqrt{\left(\frac{\left|\Delta\overline{c}\right|}{z_{Cr}^{\alpha}}\right)^2 - \left(\overline{\sigma}^{(-)}\right)^2} \tag{8.4.4}$$

The number of effectively independent (future) measurements $K_{Eff}^{(+)}$ to realise a spread $\overline{\sigma}^{(+)}$ in the estimate for the mean $\overline{c}^{(+)}$ follows from,

$$\overline{\sigma}^{(+)} = \frac{\sigma}{\sqrt{K_{Eff}^{(+)}}} \tag{8.4.5}$$

as was already extensively discussed in Appendix C. The σ in this equation is the spread in the actual future SPM measurements.

Combination of Equations 8.4.4 and 8.4.5 reveals that the number of effectively independent measurements must satisfy:

$$K_{Eff}^{(+)} \geq \frac{\sigma^2}{\left(\frac{\left|\Delta\overline{c}\right|}{z_{Cr}^{\alpha}}\right)^2 - \left(\overline{\sigma}^{(-)}\right)^2} \tag{8.4.6}$$

We must now translate $K_{Eff}^{(+)}$ to the number of SPM measurements $K^{(+)}$ that must "really" be recorded at sea. This $K^{(+)}$ can be much larger than $K_{Eff}^{(+)}$.

In the conversion $K_{Eff}^{(+)} \rightarrow K^{(+)}$ it is assumed that the future measurements are equidistant, with a constant time interval Δt between successive measurements. Compared to the past measurement sets of Noordwijk reasonable values for this Δt may then be for example a week, half a month, a month (or even larger). On the basis of the sampling interval Δt, and the auto-correlation time τ_{AC} of the SPM-process, the correlation β of successive observations can be computed. In App. C it was shown that,

$$\beta = \exp\left(-\tfrac{\Delta t}{\tau_{AC}}\right) \tag{8.4.7}$$

This correlation coefficient provides the link between $K_{Eff}^{(+)}$ and $K^{(+)}$ through

$$K^{(+)} = \frac{1 + \beta}{1 - \beta} \cdot K_{Eff}^{(+)} - \frac{2 \cdot \beta}{1 - \beta} \tag{8.4.8}$$

Combination of Equations 8.4.6 and 8.4.8 then gives the *minimal* number of measurements $K_{Min}^{(+)}$ that must be available to identify (with statistical significance) a prescribed change $\left|\Delta\overline{c}\right|$ in the means of the data sets from before and after MV2:

$$K_{Min}^{(+)} = \frac{1 + \beta}{1 - \beta} \cdot \frac{\sigma^2}{\left(\frac{\left|\Delta\overline{c}\right|}{z_{Cr}^{\alpha}}\right)^2 - \left(\overline{\sigma}^{(-)}\right)^2} - \frac{2 \cdot \beta}{1 - \beta} \tag{8.4.9a}$$

The measurement period required to collect these $K^{(+)}$ samples is $T_{Min}^{(+)} := K_{Min}^{(+)} \cdot \Delta t$, with the result:

$$T_{Min}^{(+)} = \left(\frac{1 + \beta}{1 - \beta} \cdot \frac{\sigma^2}{\left(\frac{\left|\Delta\overline{c}\right|}{z_{Cr}^{\alpha}}\right)^2 - \left(\overline{\sigma}^{(-)}\right)^2} - \frac{2 \cdot \beta}{1 - \beta} \right) \cdot \Delta t \tag{8.4.9b}$$

It must be noted that for given t_0 statistics (i.e. an estimate of the mean $\overline{c}^{(-)}$ and the spread $\overline{\sigma}^{(-)}$ in this mean), and a prior prescribed change $\Delta\overline{c} := \overline{c}^{(+)} - \overline{c}^{(-)}$ one wants to identify, the number of measurements and associated measurement period depends on:

- The significance level γ that is applied. The larger γ (and smaller $\alpha = 1 - \gamma$) the larger the amount of measurements and measurement period.
- The correlation coefficient β. This parameter depends on the auto-correlation time τ_{AC} of the SPM process, and the sampling interval Δt, see Equation 8.4.7. A larger auto-correlation time τ_{AC} will induce a longer measurement period. A larger sampling interval Δt reduces the minimum number of samples $K^{(+)}$, but the required measurement period $T_{Min}^{(+)} := K_{Min}^{(+)} \cdot \Delta t$ will increase for increasing Δt.
- The variability of the post-event SPM process, here represented by the spread σ.

8.4.2 Application to Noordwijk and Callantsoog 2 and 20 km data

For a practical and quantitative assessment of the Equation 8.4.9, all presently available measurements of Noordwijk and Callantsoog, stations 02 and 20, are considered as representative for the pre-MV2 conditions and for some variations of $\Delta\overline{c}$ the post-MV2 measurement requirements were computed on the basis of Equations 8.4.9a,b. For this application, it is assumed that the effect of MV2 on the SPM series is limited to merely a change in the mean, and the amount of variability is not changed. Hence, it is assumed that the spread σ of the t_1 SPM-measurements is the same as was derived from the t_0 measurements. It has also been assumed that thes series are stationary in statistical sense. The analysis of the fictive effect in the previous section shows that that assumption most probably does not hold for the Noordwijk 02 MWTL series where long-term trends may be present. Please note also that the 20 km data tend to agree better with the applied (exponential) model for the auto-correlation than the 2 km data.

Table 8-4 lists the statistical properties of the four series considered together with the asymptotical minimum detectable change for a significance level of 95% and an autocorrelation time (τ_{AC}) of 7 days. The determination of τ_{AC} from the ACF of the MWTL data does not allow a more detailed indication than that the auto-correlation time is below 15 days. The analysis of the ACF of the Noordwijk 02 Smartbuoy series (Figure 8-8) allows for more accurate determination of τ_{AC} of 5.8 days (at that site at least). Hence, here τ_{AC}=7 days is chosen as default.

Table 8-4 Properties of the MWTL time series of surface SPM concentration of Noordwijk (NW) and Callantsoog (CA); β is the sample correlation coefficient, K the number of samples, K_{eff} the effective number of samples (corrected for sample correlation), $\overline{\sigma}^{(-)}$ the spread in the mean corrected for sample correlation. D_{min} is the asymptotical minimum detectable change between the mean of the t_0 and t_1 series. Significance level 95%; autocorrelation time (τ_{AC}) 7 days.

	NW02	***NW20***	***CA02***	***CA20***
β	0.08	0.04	0.06	0.07
K	642	526	238	253
K_{eff}	544	478	211	219
mean $\overline{c}^{(-)}$ (mg/l)	14.6	4.3	27.6	3.5
spread σ (mg/l)	15.1	4.3	26.3	4.2
spread in mean (mg/l)	0.59	0.19	1.7	0.26
spread in mean (mg/l) corrected for β, $\overline{\sigma}^{(-)}$	0.65	0.19	1.8	0.28
relative D_{min}	8.7%	8.9%	12.9%	16.0%
absolute D_{min} (mg/l)	1.27	0.38	3.56	0.56

The dependence of the results on the choice of the significance level (γ) and the auto-correlation time τ_{AC} is illustrated below for the Noordwijk data.

Table 8-5 Minimum detectable changes of the MWTL time series of surface SPM concentration of Noordwijk 20 for significance levels γ of 90 and 95%; and autocorrelation time (τ_{AC}) of 7 and 15 days. γ=95%, τ_{AC}=7 days corresponds to Table 8-4.

NW20	γ=95%, τ_{AC}=7 d	γ=95%, τ_{AC}=15 d	γ=90%, τ_{AC}=7 d	γ=90%, τ_{AC}=15 d
β	0.04	0.07	0.04	0.07
relative D_{min}	8.9%	11%	7.5%	9.1%
absolute D_{min} (mg/l)	0.38	0.47	0.32	0.39

A first inspection of the tables above reveals that the number of post MV2 measurements depends strongly on the chosen confidence level. The measurement period is less sensitive for the sampling interval Δt. For the assessment of the mean of an SPM process high density measurements thus tend to be not really necessary. It must be realised, however, that for other purposes, as e.g. the assessment of temporal variations and/or accurate monitoring of extreme events, small sampling intervals Δt is very important. Moreover, the analysis of the Noordwijk 02 dataof the CEFAS Smartbuoy shows that the autocorrelation time τ_{AC} can be more accurate determined using high-frequency data. If τ_{AC} could have been assessed more accurately for all stations the values of the minimum detectable change D_{min} would have been lower.

Given the properties of Table 8-4 and Table 8-5, the minimum duration of future measurements can be determined in order to detect a certain change in the long-term mean. For the default setting (γ=95%, τ_{AC}=7 days), it is shown in below how many years one needs to sample with a given sample interval to detect a change of 10% to 25%.

Table 8-6 Minimum number of years (in t_1) required to assess a given relative change in the mean of the signal. D_{min}=absolute minimal detectable change given the t_0 measurements (95% confidence level, two-tailed testing). Columns represent various sampling intervals. Noordwijk stations (uncorrected for seasonal signals etc., τ_{AC}=7 days). Please note that only for the offshore stations the application of the series without any further correction for seasonal or possibly other deterministic signal components seems justified.

Noordwijk 20 MWTL Number of years

Dmin=8.9%	*sample interval (days)*		
relative difference (%)	*7*	*15*	*30*
10	78	97	158
15	11	14	22
20	5	6	10
25	3	4	6

Noordwijk 02 MWTL Number of years

Dmin=8.7%	*sample interval (days)*		
relative difference (%)	*7*	*15*	*30*
10	72	90	146
15	12	14	23
20	5	7	11
25	3	4	6

Table 8-7 As Table 8-6 Callantsoog stations (uncorrected for seasonal signals etc.)

Callantsoog 20 MWTL Number of years

Dmin=16%	*sample interval (days)*		
relative difference (%)	*7*	*15*	*30*
15			
20	16	20	33
25	6	8	13

Callantsoog 02 MWTL Number of years

Dmin=13%	*sample interval (days)*		
relative difference (%)	*7*	*15*	*30*
15	24	31	49
20	6	8	13
25	3	4	6

The effect of lowering the confidence level to 90% is illustrated in Table 8-8 below. It is clear that lowering the confidence level reduces the required number of years, or equivalently, samples. Because of the skewed shape of the density distribution of the data lowering the confidence level reduces the number of years more strongly for the relatively small changes.

Table 8-8 As Table 8-6 for Noordwijk 20 with 90% confidence level instead of 95%, τ_{AC}=7 days.

Noordwijk 20 MWTL Number of years

Dmin=7.5%	*sample interval (days)*		
relative difference (%)	*7*	*15*	*30*
10	25	32	52
15	7	8	13
20	3	4	7
25	2	2	4

In conclusion, in all cases a very (and practically speaking, probably too) long measurement periods are required to identify a statistical significant change of the means of 10%. The Callantsoog data do not even allow for detection of changes of 10%. Smaller changes in the mean cannot be identified at all, unless a very low significance is accepted.

What can be detected after 10 years?

The question of detection can be posed differently to what effect size can still be detected after, for example, 10 years of continued sampling. The minimum change that can be detected after 10 years of continued sampling for the Noordwijk 20 series is shown in below for 95% and 90% confidence level. The changes that are detectable are of the order of 15 to 20%. For the other stations similar orders of magnitude are obtained.

Table 8-9 Minimum detectable relative change after 10 years of continuation of the Noordwijk 20 MWTL series. τ_{AC}=7 days.

Sample interval (days)	Confidence level 95%	Confidence level 90%
7	16%	14%
15	17%	15%
30	21%	18%

8.5 Noordwijk 10: MWTL vs. Smartbuoy

In the discussion above, the low-frequency data of the MWTL have been used. The analysis of the CEFAS Smartbuoy data of Noordwijk 02 already showed that more information can be obtained from high-frequency data sources to more accurate determine statistical properties. For example, the auto-correlation time τ_{AC} could be assessed with more detail and turned out to be lower than the necessarily conservative choice based on the low-frequency data.

In order to assess what can be gained from high-frequency measurements compared to the MWTL data, 3 time series have been compared collected at Noordwijk 10:

1) the about 1.5 year of weekly MWTL data (March 200-Sep. 2001),
2) hourly Smartbuoy OBS data collected in parallel to the MWTL data,
3) the same Smartbuoy data sub-sampled with an interval of one week.

The graphs of these time series are shown in Figure 8-10 and Figure 8-11 below. Clearly, the CEFAS series shows much more of the intermittent peaks that occur in the SPM concentration over time. After subsampling these peaks seem to be largely removed from the CEAFS series. The averages (indicated by the dashed lines) are slightly different.

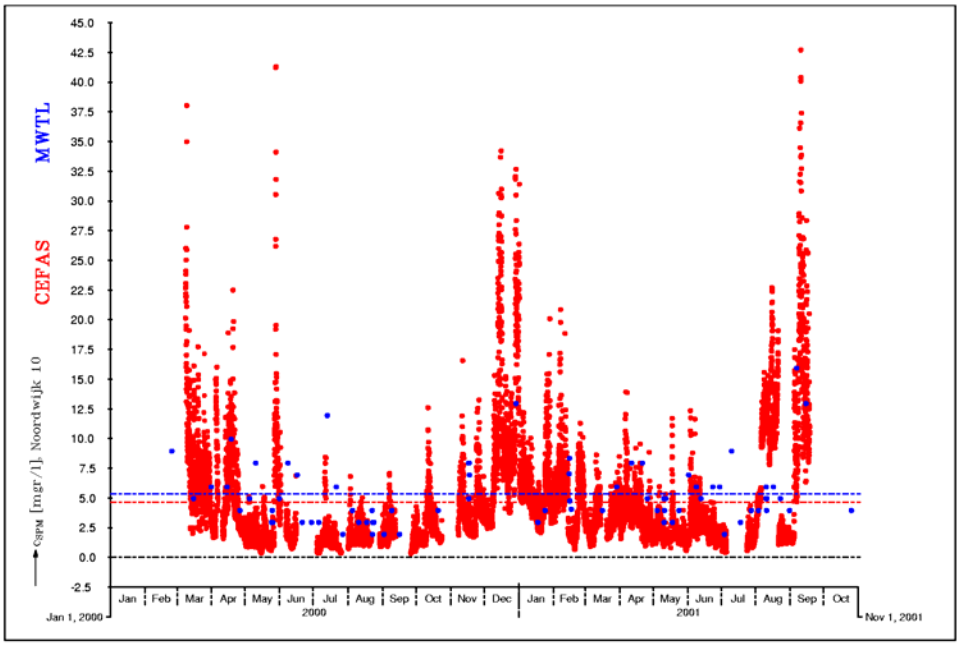

Figure 8-10 Time series of surface SPM concentration measured by the CEFAS Smartbuoy (red dots) and the MWTL *in situ* sampling (blue dots). Dashed lines indicate the means of the respective time series.

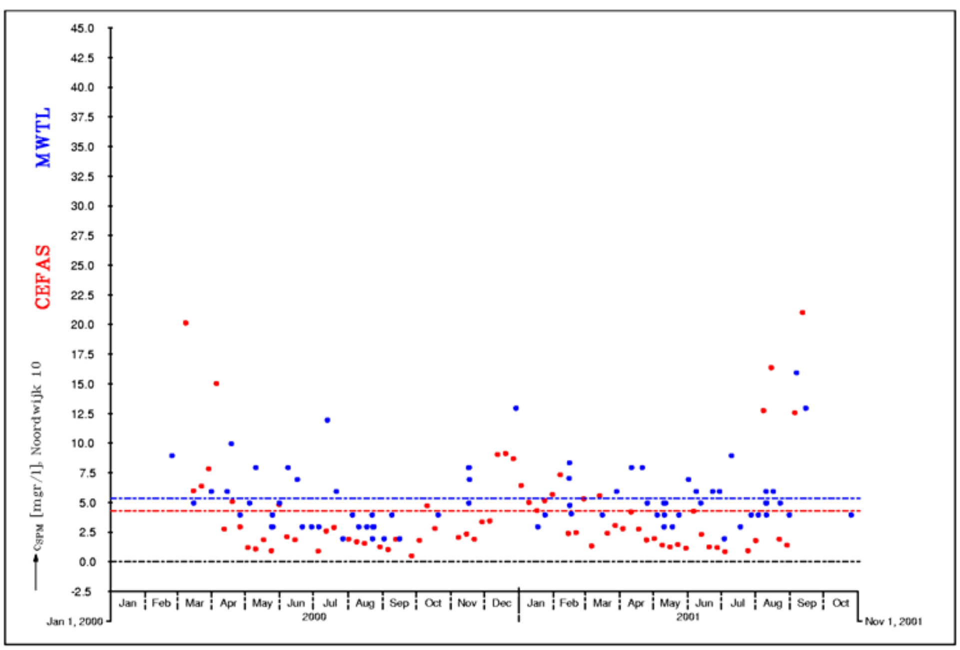

Figure 8-11 Time series of surface SPM concentration measured by the CEFAS Smartbuoy, subsampled with weekly interval, (red dots) and the MWTL *in situ* sampling (blue dots). Dashed lines indicate the means of the respective time series.

To further assess the effects of sampling frequency, the statistics of the three Noordwijk 10 series have been compared, see Table 8-10. From the analysis of the Smartbuoy series the auto-correlation time has been determined at 5.8 days, which has been applied to all three series to determine the sample correlation coefficient and the effective number of samples.

Table 8-10 Statistical properties of the 1.5 year simultaneous data series at Noordwijk 10 (Nw10). The auto-correlation time has been set at 5.8 days

	Nw10 MWTL [mg/l]	Smartbuoy (all data) [FTU]	Smartbuoy (weekly sampled) [FTU]
sample correlation coefficient (β)	0.24	0.99	0.26
nr. of samples (K)	75	11205	71
effective nr. of samples K_{eff}(corrected for β)	45.9	48.9	42.3
mean	5.4	4.6	4.3
spread	2.7	4.6	4.3
spread in mean not corrected for β	0.3	0.04	0.5
spread in mean corrected for β	0.4	0.7	0.7
minimal detectable relative change D_{min}	14.7%	27.8%	30.5%
minimal detectable absolute change $D_{min,}$	0.79	1.28	1.31

It is concluded that the means of the three series do not differ significantly, despite the different sampling techniques with possible biases and different units. This good match is partly explained from the monthly (re)calibration of the OBS to the in situ data . Moreover, the comparison of the data from Noordwijk 10 from both the MWTL and Smartbuoy shows that decreasing sampling interval does not provide a reduction in minimal detectable change. This is due to the fact that the auto-correlation time is about 6 days and because the corrected spread in the mean of the data of the Smartbuoy is larger than in the MWTL data. The subsampling confirms that this larger spread in the Smartbuoy data is not an artifact of the sampling frequency. It may be speculated that the sampling method of the MWTL leads to an underestimation of the spread in a given SPM signal (detection limits, biased sampling, etc.)

The comparison of the data from Noordwijk 10 from both the MWTL series and the full Smartbuoy series shows that decreasing sampling interval without any further post-processing of the data does not provide a reduction in minimal detectable change. This is partly due to the fact that the auto-correlation time is about 6 days and hence reduces the effective number of samples of the Smartbuoy to about 0.4% of the original number, More importantly, the corrected spread in the mean of the data of the Smartbuoy is about 1.7 times a large as the MWTL data. All together, the Smartbuoy series results in an almost twice as large minimal detectable change.

Subsampling of the Smartbuoy series with a weekly interval confirms that the larger spread in the Smartbuoy data is not an artifact of the sampling frequency: one does not accidentally miss the peaks in the signal and thus reduce the spread if one would sample in an unbiased way every week. It may be speculated that the sampling method and policy of the MWTL leads to an underestimation of the spread in a given SPM signal. For the MWTL data the minimal detection limit is at lowest 1 mg/l whereas the OBS of the Smartbuoy frequently reports to ten times lower values. Moreover, the ship-based sampling is probably biased towards relatively calm weather conditions. It is important to realize that these shortcomings most probably apply to all MWTL ship-based data (see Blaas et al, 2006 for a more elaborate discussion).

8.6 Correcting Smartbuoy data for wave and current effects

The high-frequency data of the Smartbuoy at Noordwijk 10 are expected to contain certain deterministic signal components that may contribute to the still relatively high sample correlation coefficient. A time series plot of the Smartbuoy data shows intermittent peaks of up to five time the mean of the series that last a few days (see also Figure 8-10). Part of the SPM signal at the Smartbuoy is determined by advective (partly tidal) transport from elsewhere which is impossible to determine from a point measurement that offers insufficient information on current fields and concentration gradients. Nevertheless, currents due to tides and winds and especially waves also contribute to the local resuspension of sediments on the sea floor. The availability of both high frequency SPM data and wave data offers the opportunity to further process the data in relation to these known physical influences on the SPM concentration.
A 1DV model has been developed that parameterizes the effect of tidal currents and waves on the bed shear stress which is responsible for the resuspension of sediment. In this model it is assumed that a local, equilibrium exists between the bed shear stress, vertical settling and the tendency of near-surface SPM concentration. The erosion rate coefficient, settling velocity and partitioning between the two bed layers, which are an ill-known parameters in the field have been used to calibrate the model such that it reproduces the magnitude of the peaks well enough while also capturing the mean conditions.

The model has been applied to the 2001 part of the Noordwijk 10 Smartbuoy time series. Figure 8-12 shows the time series of the observations, the model and the residue in the observations after subtraction of the model prediction. Clearly, the model captures many, though not all, of the peaks as well as the lower values in between.

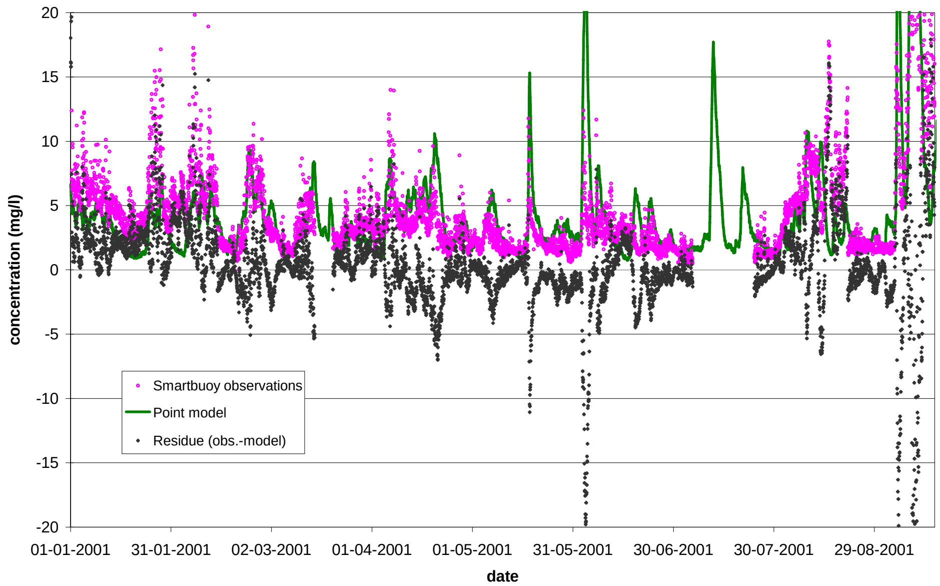

Figure 8-12 Time series of part of Smartbuoy data at Noordwijk 10 for 2001 (magenta dots), along with the prediction of the 1DV model driven by waves and currents (green curve) and the residue (the difference between observation and model, black dots).

Te auto-correlation functions (ACF) of the original Smartbuoy series and the residue are shown in Figure 8-13 and Figure 8-14, respectively. Periodicities in the signal appear to have been removed and the ACF close to τ=0 has become much steeper which indicates that the signal has become more stochastic.

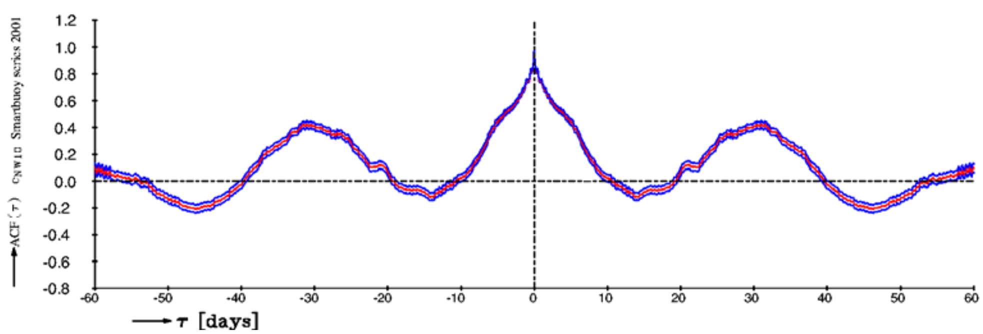

Figure 8-13 Autocorrelation function of original Smartbuoy series at Noordwijk 10 for 2001.

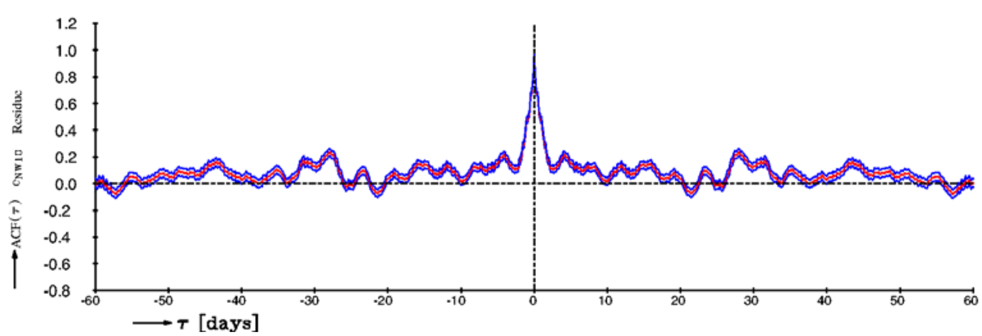

Figure 8-14 Autocorrelation function of the residue obtained after subtractionof the 1DV model time series from the Smartbuoy series at Noordwijk 10 for 2001.

The statistical properties of the original time series are displayed in Table 8-11. Most importantly the auto-correlation time (τ_{ac}) of the residue is over four times smaller than of the original series. This reduces the sample correlation coefficient and increases the effective number of samples by a factor of about four. As may be expected, the mean of the residue is closer to zero than the original series but also the spread in the residue is reduced due to the model. Combined with the larger effective number of samples this reduces the corrected spread in the mean, and, similarly, the minimal detectable change with more than a factor of two. Figure 8-15 shows the dependence of the reduction factor of the number of samples on sampling interval and auto-correlation time. It can be seen that for higher-frequency data the relative gain from reducing the auto-correlation (e.g. by means of signal processing like the present example) is much higher than for low-frequency data.

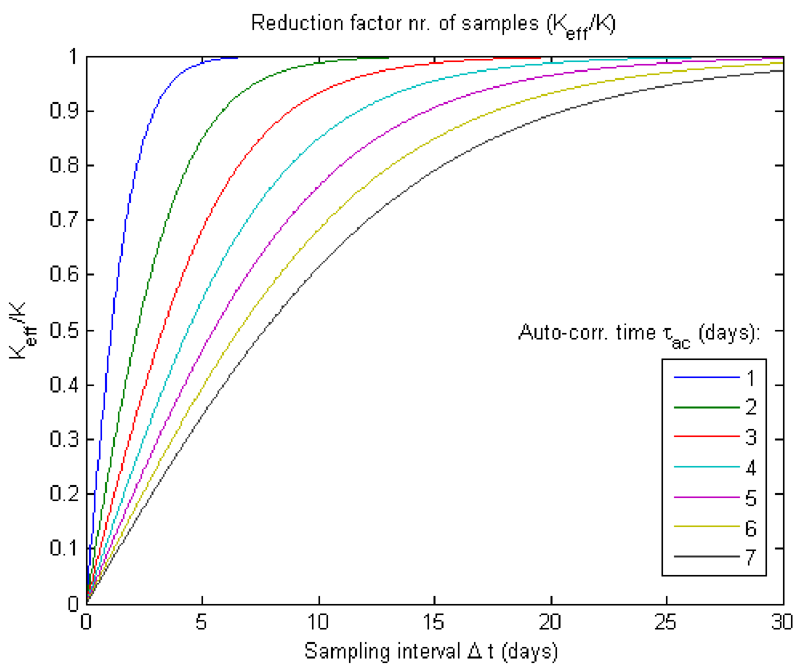

Figure 8-15 The reduction factor of the number of samples K_{eff}/K as function of mean sampling interval Δt and auto-correlation time τ_{AC}.

A future time series (t_1) can be subjected to the same exercise in which the 1DV model (in prediction mode) removes the part of the deterministic signal and the hypothesis of no change can be applied to the unexplained residue before and after MV2. Still, for every model it has to be decided whether or not the forcing (input) itself may contain MV2 effects in future (in the case of waves at Noordwijk10 this is unlikely). Also, the interpretation of any differences in the residue in terms of the cause (also in the context of the model) requires careful attention (e.g. the local sediment bed properties may be autonomously changed or downstream supply of sediment may be different irrespectively of MV2)

Table 8-11 Statistical properties of the 2001 Smartbuoy data series at Noordwijk 10 compared to its residue after removal of wave and tide effects.

	Smartbuoy (2001 data) [FTU]	Residue Smartbuoy (1DV model subtracted) [FTU]
auto correlation time (τ_{ac})	5.8 days	1.25 days
sample correlation coefficient (β)	0.99	0.96
nr. of samples (K)	5672	5672
effective nr. of samples K_{eff} (corrected for β)	23.29	105
mean	4.5	0.29
spread	4.13	3.6
spread in mean not corrected for β	0.055	0.048
spread in mean corrected for β	0.86	0.35
minimal detectable absolute change $D_{min,\ abs}$	1.68	0.69

9 Additional techniques

From the preceding chapters it has become clear that the success of the approach proposed depends to a large extent on the detailed characteristics of the data taken into account and on the nature and magnitude of the changes that may occur in future. The 'success' in this respect is depending on the significance with which changes can be determined from the data and, if so, with what degree of certainty the changes can be attributed to the MV2. For this latter issue the system functions are essential, although the question remains if they will be sufficient.

To supply additional data for level I and II hypotheses, to construct system functions for level III tests, and to further support the identification of MV2 effect in distinction from other simultaneous changes, additional deterministic modelling techniques may come into play. A deterministic SPM transport model forced by observed MV2-independent data (*e.g.* winds, waves, SPM boundary conditions) can be used to set up hindcast experiments in which the only difference between twin experiments is the presence or absence of the extended MV2. In this way insight in the response of the coastal system can be obtained *a posteriori,* and consistency of system relations can be assessed.
In addition, Data Model Integration (DMI) can be applied. Data-assimilation techniques such as relaxation, Kalman Filtering, 3D or 4D VAR and application of adjoint models allow to incorporate observed temperature and salinity data and, possibly, even observed SPM data to simulate the transport in the coastal river. This not only provides means to spatially and temporarily interpolate observed data but it also provides data not measured: *e.g.* the vertical structure of concentration fields and data on current velocities. Hence, actual instantaneous and residual fluxes can be determined that cannot from field data alone. These data may be added to the data sets considered for testing.

10 Conclusions, outlook

The present report presents an approach to assess changes in the SPM transport system in the Dutch coastal zone due to the extension of the Maasvlakte (MV2). Based on current system knowledge, the following methodology is proposed:

- Divide the Dutch coastal area into four areas:
    - one area directly surrounding the Maasvlakte 2 (MV2) which is not considered in further detail other than that it is a source of possible changes in the SPM transport
    - one area well south of the MV2 (off Zeeland and further to the south) where only autonomous changes are expected (if any)
    - two areas north of the MV2 (Holland coast and Wadden area) where both autonomous and MV2-related changes may occur.
- Use data available from these areas (measured during t_0 and t_1) to assess whether or not significant changes in the mean and in derived statistical properties of relevant measures for SPM transport have occurred.
- Design and analyse system relations (based on t_0 data) between various measures of SPM transport or forcing conditions, and within and between the various areas. By selectively testing the preservation (with sufficient significance) of these relations after MV2, conclusions can be reached on whether or not any observed change is due to MV2. For example a relation between wave stirring and SPM concentration may be formulated to assess whether a long-term variation in SPM is attributable to any observed long-term variation in wave conditions.

The approach relies on the notion that an undisturbed area can be defined south of MV2 which serves as a reference in the future. This reference is needed to help distinguish changes due to MV2, in the area north of MV2, from other (autonomous) changes in the system. Secondly, the approach relies on the availability of sufficient data in time and space and of sufficient quality in all areas of interest (which is not only the area in the direct vicinity of the MV2). The question on what is 'sufficient' can be partly addressed by means of the examples with the stations on the Noordwijk and Callantsoog transects.

In a first example it has been tested whether the mean of two parts of the present SPM time series of Noordwijk 2 and 20 of nearly equal length (obtained after splitting the series at January 1, 1993) are significantly different or not. It was found that for Noordwijk 2 the mean of the series after 1993 was significantly lower by 22% (i.e. 12.8 instead of 16.4 mg/l). It is not clear what is the cause of this change. Autonomous interannual changes in waves, winds, or currents may play a role, but also systematic changes in measurement protocol may be a cause. Moreover, applying the same test to the Noordwijk 20 data showed an insignificant reduction in the mean. Further investigation of the causes and exploration of the dependence on location is beyond the scope of the present study. At least it is concluded that these type of properties of the data limit their usefulness. Further study would be required to reduce the biases by proper correction for objectively identifiable systematic changes in forcing or data collection etc.

In a second example it has been determined what the minimal requirements (in terms of number and duration of measurements) in the t_1 situation are in order to detect a given change in the mean. The requirements depend strongly on the variance in the t_0 and t_1 signal and the desired significance. Both a lower variance and a larger number of statistically independent observations reduce the spread in the mean of a series. The number of independent observations in turn depends on the autocorrelation time and sampling interval of data series. For the SPM surface concentration it turned out that without any further processing autocorrelation times are in the order of 5 to 7 days and the spread of time series is on te order of the mean. This implies that the time span of detecting significant changes by continuing weekly sampling is of the order of several years (about 2 to 5 years for a relatively large effect of 25% to over 50 years for an effect of 10% or less). For lower sampling frequency (up to monthly) the required time span increases less than proportionally. On the other hand this time span is not reduced much further when sampling hourly, like the Smartbuoy data that have also been analysed. This is due to the autocorrelation time on the order of days. Analysis of the Smartbuoy data further showed that variance of the high-frequency series was even higher than of the low-frequency series and that this was not due to sampling frequency. It is speculated that this is due to measurement and surveying protocol (e.g., in situ data may be biased towards calm weather and have different lower detection limits).

Despite the apparently low gain of accuracy in the determination of the mean, the use of high-frequency data nevertheless offers advantages (i.e., high-frequency with respect to the auto-correlation time).

- The auto-correlation time of a given time series determines the total time required to assess certain changes can be assessed the more accurately using high-frequency data.
- The data series can be further corrected for deterministic signal components which reduce the variance and auto-correlation. The higher the frequency of not only input data but also the target data, the more accurate correction-model parameter can be assessed.
- An eventual reduction of the autocorrelation time is more profitable the higher the sampling frequency.
- Determination of other statistical properties (time lags, exceedance, quantiles) will be more accurate for higher frequency data.

While assessing a change is the first step, the second step is to discern the cause of the change. It depends on the system relations that relate SPM concentrations of the area of interest to the reference area and possibly include additional forcing conditions whether discerning the cause is feasible. Stochastic relations are required with sufficient predictive power given the present and future data. A more extended study would be required to assess the full usability of all data available. At present it is difficult to fully anticipate on developments in data collection (especially retrieval of Remote Sensing data and their combination with in situ data, but for example also developments in quasi-continuous measuring of SPM fluxes using ferry boxes). Besides, there will be a continuing development of insight in the system. Especially the details of the formulation of system functions (which variables to include) depends the state-of-the art insight into the system by that time.

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A Logic of the approach

A.1 General scheme of testing strategy

Below is a scheme that illustrates the sequence of testing the hypotheses with respect to reference conditions (Level I), conditions north of MV2 (Level II) and system functions (level III). Tests of level II may be done also for spatial sub-domains, so that in combination with assessment of the data insight in the nature of a change is obtained. Testing of system functions may be done selectively, depending on the results of the tests on Levels I and II and the general data analysis. Testing at level III may result in some system functions being preserved, others being rejected.

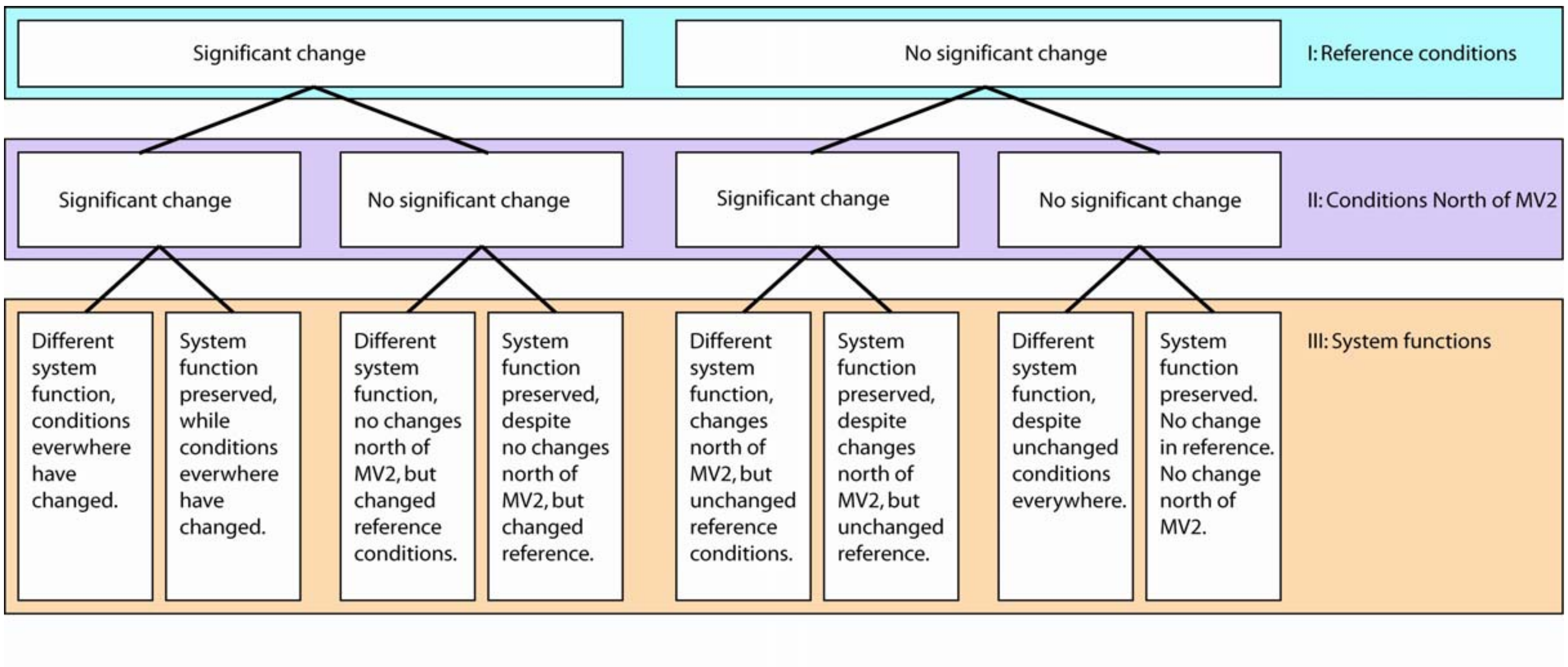

Figure A-0-1 Scheme applicable to testing of the hypotheses of level I, II and III presented in Chapter 3.

A.2 Comments to logic

To further explain the logic, the four main scenarios are illustrated below.

A.2.1 No change in reference conditions, no change north of MV2.

In the event that all hypotheses of type I and II are not rejected, the conclusion is that no significant change whatsoever could be demonstrated given the variables investigated. Hence, no effect of MV2 could be significantly demonstrated. It seems very unlikely that validated system relations then will be rejected and formulating and testing them seems unnecessary.

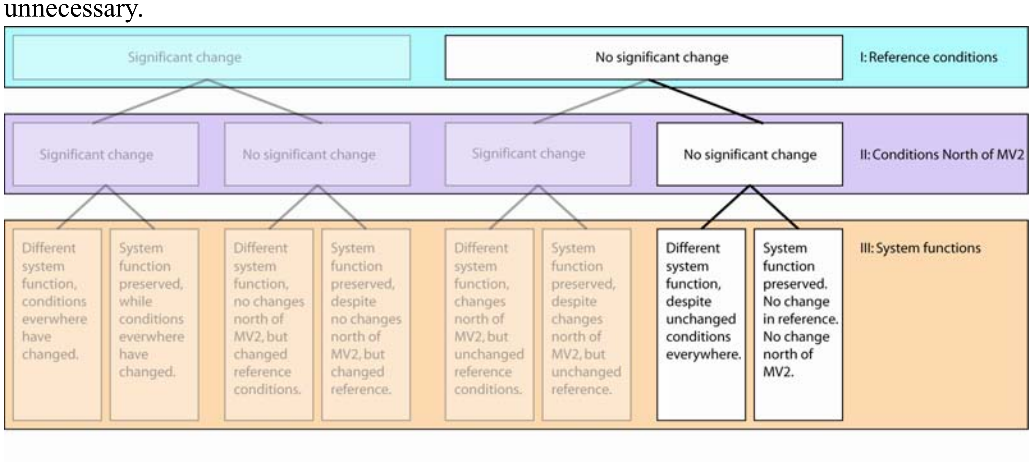

Figure A-2 Scenario of no significant change in reference conditions, nor in conditions north of MV2.

A.2.2 No change in reference conditions, change north of MV2.

If the reference conditions do not change significantly but there are significant changes observed north of MV2, the questions arises whether these are to be attributed to MV2 or to other simultaneous changes in the system. The system functions should be designed to clarify this as far a possible. It is very unlikely that all system functions are preserved. For example the functions relating concentrations of Area C to A are expected to be rejected if the conditions in C change and conditions in A do not. The more the system functions relating other factors to SPM are preserved, the better the changed signal can be explained from models using the (changed) forcing as input and the less likely the change is due to MV2. If, on the other hand, more functions related to forcing conditions break down, the more likely the change is due to MV2. For example the relation between SPM concentration in a particular area and Nieuwe Waterweg and Haringvliet discharges may break down because of the introduction of MV2. Nevertheless, in such a case it remains difficult to quantitatively assess which fraction of the change is merely due to MV2 and which fraction is due to changes (if any) in river discharges.

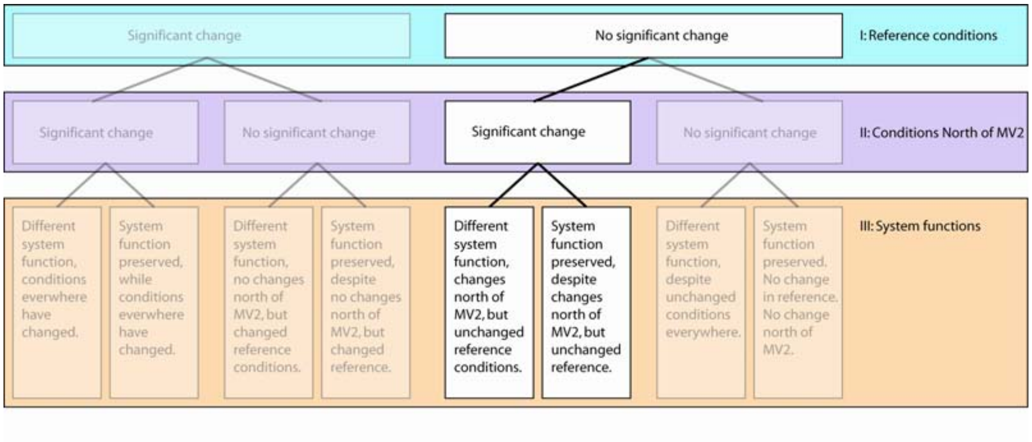

Figure A-3 Scenario of no significant change in reference conditions, but with a significant change in conditions north of MV2.

A.2.3 Change in reference conditions, no change north of MV2.

If a significant change in reference conditions is observed but no significant change in conditions north of MV2 is found, then the change in area A may either not be representative for conditions further north (assess from testing relations between A and C for increasing distance (in space and/or time), changes may not penetrate far north), or be compensated (or at least obscured) by other changes in the system. These are only assessable if other system functions are preserved and thus explain the observed signal. In any case, no significant changes are observed (e.g., at least north from a certain distance from MV2), so the questions whether or not effects can be attributed to MV2 appears less relevant.

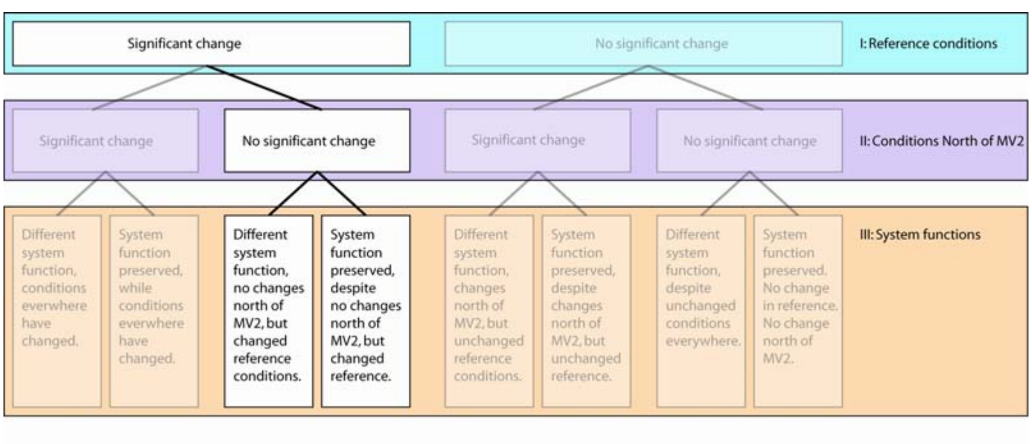

Figure A-4 Scenario of a significant change in reference conditions, but without significant change in conditions north of MV2.

A.2.4 Change in reference conditions, change in conditions north of MV2.

If simultaneous changes occur south and north of MV2 it depends on the system functions whether or not MV2 effect can be discerned from other effects. If system functions that relate SPM concentrations in area C to MV2-independent forcing conditions are preserved because their predictions do not differ significantly from the observed signal, the effect of MV2 appears minor. If on the other hand, all sensible system functions that incorporate MV2-independent terms fail, the system with MV2 behaves so much differently that an effect of MV2 appears not unlikely.

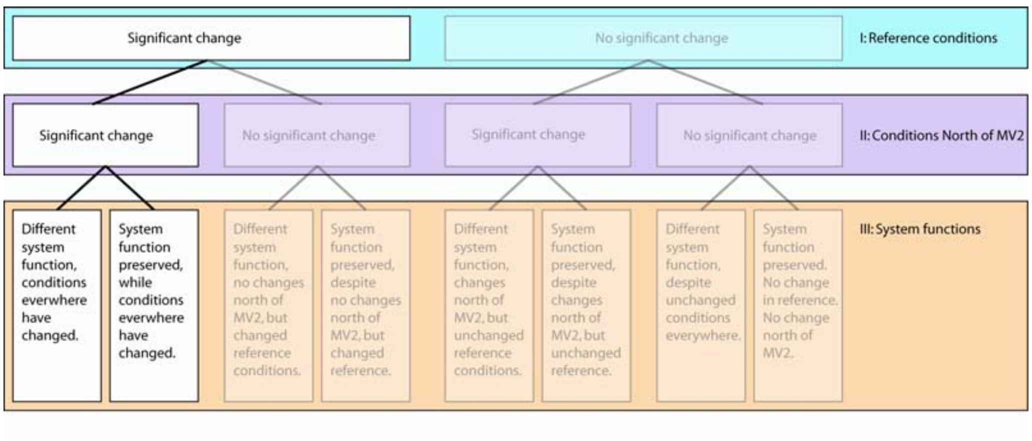

Figure A-5 Scenario of a significant change in reference conditions, and significant change in conditions north of MV2.

Details of the statistical methods

B.1 General introduction

In the formulation of mathematical techniques for evaluation of the hypotheses different levels of spatial "resolution" or "aggregation" will be distinguished. In fact, in Section B.3 we will consider methods for observed SPM-data (time series) from single/individual spatial positions. Next, in Section B.4, methods are formulated for the relation and spatial distribution of data of neighboring and more or less (geometrically) strongly related locations, with in particular the clusters of measurement positions located on cross-shore transects (such as Noordwijk, Egmond aan Zee, Callantsoog, etc.). In Section B.5 methods and system relations are considered dealing with the interaction of SPM measurements of geometrically remote positions. Finally, Section B.6 deals with high-resolution, spatially distributed data as recorded by satellites.

B.2 Considerations

First some notes and general comments are formulated about the scope, background, motivation, aim, assumptions/restrictions, etc., of the approaches that are proposed.

B.2.1 Statistical consistency of data before and after MV2 construction

The basic idea for the formulation of the hypotheses, and the mathematical procedures to verify these hypotheses, is that observations before MV2 (in the remainder referred to as "t_0 observations") are used to derive statistics and/or identify parameterised models ("system relations"). Estimates for uncertainties in these statistics and system relations are quantified as well. On the basis of these statistics and uncertainties it can then be tested whether or not observations after the MV2 construction ("t_1 observations") are statistically consistent with the t_0 statistics and/or system relations that represent the system without MV2.

B.2.2 Spatial coverage and temporal density of observed data

To obtain statistically meaningful results in such an MV2-impact assessment, observed data sets must be available that cover a time span of at least a few years. Within each year (or month) sufficient samples should be present to reflect (and/or identify) the main temporal dynamics of the processes such as seasonal variations and/or longer-term variations and trends. Such variations and trends will probably not cease after an extension of MV2, but are likely to proceed unaltered. Therefore it must be taken into account that observed changes in the SPM transport after an extension of MV2 can "merely" be an after-effect of ongoing long term processes, rather than a strict response of the (North Sea) system to the new MV2-topography.
Similarly, a large and sufficiently dense spatial coverage of data sets ("distributed data") may be required as well to address questions and hypotheses related to the spatial range (length scales) and properties of the impact of an MV2 extension.
While in situ measurements tend to be most suitable for the assessments of temporal properties (and changes due to MV2) of the transport and spread of SPM along the North Sea (and particularly along the Dutch "Coastal River"), remote sensing images are expected to reflect in more detail the spatial properties of SPM distributions.

B.2.3 Uncertainties in data, models, and estimates

SPM dispersion and transport are complex dynamical processes and are affected by a variety of "external" factors or forcing such as meteorology, waves, river discharges and sediment loads, bed and flow properties, etc. Apart from a systematic behaviour such as seasonal variability and/or longer term trends, observed SPM-data series often exhibit irregular short term temporal and spatial fluctuations as well, suggesting (temporally and spatially short term) random effects. Therefore *uncertainties* are an important aspect in the (statistical) description and/or modelling of such data. Particularly this is the case for the present hypotheses and their verification. To deal with these uncertainties appropriately, Maximum Likelihood (MLH, se e.g. Kendall and Stuart, 1961) based formulations of the hypotheses are advantageous. The reason is that in this way estimation procedures can be applied that provide quantitative and theoretically sound estimates for uncertainties in system relations. These estimates for the uncertainties can in their turn be used for testing or verification of the hypotheses, for example when dealing with 'new' data such as t_1 measurements, and checking whether these are statistically consistent with the t_0 conditions. Therefore a number of the hypotheses formulated in this manuscript are based or inspired by MLH. For completeness it is noted that MLH (in combination with Gaussian models for the uncertainties) is closely related to least squares estimation procedures, as often applied in regression models. These may comprise of ordinary least squares estimation procedures (as e.g. mentioned by Duin et al. 2005) or generalised weighted least squares criteria that are encountered when uncertainties are non-uniform or non-stationary.

B.2.4 Scaling and/or transformation of observed SPM-data

In the preceding remark it was mentioned that (e.g. when using MLH based formulations of hypotheses) Gaussian (normal) distributions of data and/or uncertainties facilitate the identification and uncertainty assessment of hypotheses and/or system relations. SPM-data will usually not satisfy a normal distribution. In fact, in their comparison of in situ and satellite observations Duin et al. (2005a,b) report lognormal distributions instead. Therefore they applied a log transform of the data and on the basis of the transformed data a stochastic model of the data was proposed and identified using an (ordinary) least squares criterion. Such a (non-linear) scaling of the data must be (re)considered as well when the here proposed hypotheses and system relations are actually evaluated. At this moment we will not pay further attention to this issue and merely note that this should be carefully considered later when the data are collected and their properties and distributions are evaluated. In particular it can then be verified in further detail whether to use a log transform, or rely on alternative and/or more general scaling procedures such as a Box-Cox transformation of the data, see e.g. Box and Cox (1964) or Davidson and MacKinnon (1993). The Box-Cox transformation includes the log transform as a special case.

B.2.5 System relations and measurement locations

Some of the hypotheses formulated are based on so-called system relations. Such system relations are actually (parameterised) transfer function models where the time series of SPM at one location (as output of the model) is predicted from the series of another location (as a model input), and/or other inputs consisting of time series of the main external system forcing as for example wind velocities, waves, discharges by rivers, or other sediment "boundary" conditions. The amount of correlation between the input and output series determines the accuracy of such a system relation. The higher the accuracy of the system relation, the better impacts and statistical significance of an MV2-extension can be identified. In a wider sense accurate system relations may provide other important opportunities. The optimisation of measurement locations can be mentioned as a relevant practical example. Except for a very few locations, the SPM-concentration is now sampled with a relatively low temporal density of about 1 to 2 samples per month. Important information about short-term fluctuations can then be missed. On the basis of system relations it may then be verified which positions are most important for observations with a high temporal sampling density, and how to translate/transfer this information to other locations with a less dense sampling rate, or where measurements are fully absent.
This issue is also relevant for the present case when deciding where before and after the extension of MV2 (extra) measurement locations must be positioned.

B.2.6 Concentrations and/or fluxes

In the description of the various hypotheses the mathematical expressions will mainly be formulated in terms of an SPM concentration denoted by the symbol c. This c can represent a concentration in the strict sense, i.e. the concentration $c(\vec{r},t)$ at a particular time t and spatial coordinate $\vec{r}$. For many of the hypotheses an aggregated or averaged form of the SPM-concentration can also be adopted for c, as for example a depth averaged concentration, or the average over a horizontal transect, and/or an average over some time period (as e.g. monthly or seasonal means). More generally the c symbols in the formulas can also represent an SPM-(mass)flux through a 1D (horizontal or vertical) transect, or 2D surface.

B.3 Univariate methods for individual locations

B.3.1 Evaluation and comparison of "elementary" statistics

In this section some "simple" and/or "elementary" statistical measures are summarised that can be used for a closer assessment of the distribution and properties of an observed SPM-time series at a particular spatial position. Although these statistical measures are computed for single positions, an ensemble of these quantities computed for different spatial positions can provide insight in spatial dependencies and spatial variability.

B.3.1.1 Auto-correlation functions and Harmonic Analysis

By means of auto-covariance and/or auto-correlation functions (see e.g. Chatfield, 1980) properties of the temporal evolution of an SPM time series observed at some spatial position can be inspected. The correlation functions can be applied to the original observed time series, or to a series of residuals that is found after removing a trend in the series. In this way indications of possible seasonal components and/or trends become available, as well as estimates for the temporal memory scale(s) in the process. Such correlation functions can be derived and compared for both t_0 and t_1 observations. It is doubtful, however, whether on this basis significant conclusions can already be derived about the effect of MV2. Therefore, the main object of this auto-correlation analysis is to obtain further insight in the properties of the SPM-data which can be of help in the formulation and verification of other hypotheses.
Similar to the auto-correlation functions a spectral (harmonic) analysis can be applied to assess in further detail the main (temporal) components in the SPM-time series of a certain spatial position.

B.3.1.2 SPM distribution functions, quantiles, and probabilities of (non)exceedence applied to subsets

For a particular position with sufficient SPM observations all available and validated t_0 measurements are collected. Subsets are constructed, for example on the basis of a season. For a selected subset the probability distribution of this subset is determined. This distribution can be the empirical distribution, i.e. a frequency distribution in the form of a standard histogram, or a suitable analytical probability distribution function fitted to the samples that were selected. For the same season the t_1 measurements of the same spatial position will be selected as well. For each t_1 measurement the distribution function based on the t_0 measurements is used to derive a probability of exceedence. In case that this probability of exceedence is rather low (for example less than 5%) or quite high (e.g. greater than 95%) for a non-proportionally large number of the t_1 samples, there is evidence for a systematic MV2-effect. More or less equivalently this means that for a given "confidence level" α (e.g. 95%) the $(1-\alpha)/2$ (2.5% if $\alpha=0.95$) and $(1+\alpha)/2$ (97.5% if $\alpha=0.95$) quantiles of the t_0 distribution are computed. These quantiles may be seen as the end points of the α-confidence interval. Next the number t_1 samples is counted that are outside this confidence interval. It must then be verified statistically whether this number is significant or not. This recipe can be applied whether the number of t_1 samples is small or large. In case the number of t_1 samples is also high, a "complete" probability distribution function can be identified for the t_1 samples as well, and other statistical procedures can be applied (as e.g. a run test) to verify whether the t_0 and t_1 distributions are mutually consistent or significantly different.
In case an t_1 sample is found to be significantly different from an ensemble of corresponding t_0 observations, it must additionally be verified whether this difference is really the result of an MV2-extension, or "merely" due to completely different system conditions (river discharge and river sediment load, extreme storm or wave events, etc.) during the t_0 and t1 measurement periods.

The preceding recipe can be repeated for other locations and/or seasons where SPM-obervations are available before and after MV2. Moreover the procedure may be applied to aggregated data, e.g. the vertically averaged (or lumped) SPM-measurements at a particular horizontal position, or concentrations averaged or lumped from nearby spatial positions.

B.3.1.3 Distribution functions, quantiles, and probabilities of exceedence applied to extremes

The idea is the same as outlined above in B.3.1.2, but now the t_0 and t_1 extreme values are selected for a particular season (or yearly extremes). A proper extreme value distribution is identified for the t_0 samples, and the probabilities of exceedence of t_1 samples are computed and verified for statistical significance.

B.3.2 Model based analysis, prediction, and verification

B.3.2.1 General concepts

In this case an approach very similar to the one proposed and applied by Duijn et al. (2005a, 2005b) can be followed which in effect means that a historical time series of t_0 observations $\{y_t\}_{t=1}^{T}$ is described by a parameterised stochastic model. Quite generally such a model may be of the form:

$$y_t = \Phi(t \mid \Theta) + V_t \qquad \text{(B.1)}$$

The $\Phi(t \mid \Theta)$ denotes a deterministic component of the model and in physical terms this $\Phi(t \mid \Theta)$ represents the dominant "systematic" temporal variations in the time series. The Θ are one or more (uncertain/unknown) parameters in the mathematical description of this deterministic component. In the deterministic part of the model the seasonal variations may for example be included. In that case $\Phi(t \mid \Theta)$ can be modelled by a periodic function of time and most conveniently this is achieved by a (truncated) Fourier series of the form:

$$\Phi(t \mid \Theta) = \Theta_0 + \sum_{n=1}^{N} \left(\Theta_{2n-1} \cdot \cos\left(2\pi \cdot n \cdot \tfrac{t}{T}\right) + \Theta_{2n} \cdot \sin\left(2\pi \cdot n \cdot \tfrac{t}{T}\right) \right) \qquad \text{(B.2)}$$

See also Duin et al. (2005a, 2005b). In the present case the period *T* will be one year. The *t* is a continuous time coordinate and may for example be expressed in days. Apart from the seasonal variations it may also be necessary to account for (systematic) longer-term variations, such as trends in the series that extend over several years. Mathematically such a long-term trend (i.e. a systematic increasing or decreasing behaviour in the series) can conveniently be described by a low degree polynomial expression leading to

$$\Phi(t \mid \Theta) = \Theta_0 + \sum_{m=1}^{M} \Theta_m \cdot \left(\tfrac{t}{T}\right)^m \qquad \text{(B.3)}$$

For M=1 the trend is then described by a linear function. For M=2 it is parabolic function while for M=3 it is a cubic polynomial expression.
In general the function $\Phi(\cdot\,|\,\Theta)$ in Equation B.1 will be a superposition of the right hand sides of equations (B.2) and (B.3) to account for the presence of both seasonal variations and long term trends. In that case the total number of model parameters is $2\cdot N+M+1$.
The V_t in equation (B.1) is a zero mean random noise that represents all non-systematic (short term) temporal and/or local variations of the observed SPM series, not 'explained' by the deterministic component $\Phi(\cdot\,|\,\Theta)$. In the ideal case V_t is a stationary white Gaussian random process. The Gaussian property may be achieved by a proper scaling of the observed SPM series as reported by Duin et al. (2005a,b). In fact, they noted a lognormal distribution for observed SPM concentrations and therefore applied a log transformation to the data. More generally Box-Cox transformations (Box and Cox, 1964) may be applied if necessary. Stationarity of the noise is then not yet guaranteed and the spread σ of the noise V_t can still depend on time. This so called heteroscedacity[4] must then also be taken into account by means of a proper parameterisation of the spread or variance of V_t. In practice it is often observed that the uncertainty in a quantity is proportional to its magnitude and in that case $\sigma_t=\lambda\cdot y_t$ provides a reasonable parameterisation of the spread σ_t of the noise V_t. The λ is a constant but usually unknown (model)parameter whose value must be estimated from the data.

Observations of SPM-concentrations tend to be at a frequency of about two samples per month or even less. It is expected that this sampling period is larger than the auto-correlation time of the (random) fluctuations of the concentrations. In that case it can well be assumed that V_t is a *white* noise (i.e. a random process without temporal memory). Otherwise a (statistical) model for the auto-correlation function of V_t must be defined as well. An exponential form with the auto-correlation time τ as an uncertain parameter in this function could be suitable. This τ (as well as the parameters in the representation of a non-constant spread of the noise V_t, as for example the λ in $\sigma_t=\lambda\cdot y_t$) is then an other unknown model parameter and can be augmented to the other uncertain parameters Θ in the deterministic part of the model.

The preceding leads to a parameterised model for the SPM time series at a certain spatial (horizontal and/or vertical) position. The next step is to identify the model's parameters Θ using a data set of observed SPM. Using a Maximum Likelihood (MLH) criterion this means that a (minus Log-likelihood) function $L(\Theta)$ must be minimised with respect to Θ (see e.g. Kendall and Stuart, 1961). For the parameters in the deterministic part of the model this function is equivalent to a *least squares criterion*. For the so found estimate $\hat{\Theta}$ of the parameters, the MLH-methodology also provides an estimate for the covariance matrix Γ of $\hat{\Theta}$, from which in particular spreads can be computed. These spreads are a measure for the uncertainty in the estimate $\hat{\Theta}$. In case of sufficiently large data sets it will hold that Θ

[4] *In statistics a sequence of random variables is heteroskedastic if the random variables in the sequence may have different variances The complement is called homoskedacity. In US it is usually spelled* homoscedastic.

satisfies a Gaussian distribution with mean $\hat{\Theta}$ and Γ as covariance matrix. On this basis symmetric confidence intervals can be constructed for the estimates $\hat{\Theta}$ of the parameters. In case of small observation sets, however, the distribution of $\hat{\Theta}$ need not to be Gaussian and can be highly skew. Confidence intervals will then be skew as well, meaning that the mean is not the middle of the lower and upper bound of the confidence interval. Such non-symmetrical confidence intervals can hardly or not be computed in analytical form and numerical approximations or alternative strategies must be applied. Resampling techniques are an important example of such an alternative and theoretically sound method for the computation of skew confidence intervals (see e.g. Efron and Tibshirani, 1993). The main issue in resampling is that an estimation procedure is repeated many times with the result that a large set of estimates becomes available for Θ, and from this set of estimates skew confidence intervals can easily be computed. To obtain such a large set of estimates, replicates (so called resamples) are constructed from the original data set. Each resample is thus a subset of the original data set. Some data points of the original data set may then be absent in the resample, while other data points may be present more than once (and in this way represent a larger weight in the resample). For each resample the estimation procedure is repeated leading to an *ensemble* of estimates $\left\{\hat{\Theta}^{(\ell)}\right\}_{\ell=1}^{L}$ (L is the number of resamples constructed from the original data set, and $\hat{\Theta}^{(\ell)}$ is the estimate of Θ based on the $\ell-th$ resample). The advantage of resampling is that in this way an (empirical) probability distribution is obtained for the model's parameters Θ. This distribution needs not to be Gaussian, however. In any case it provides a complete statistical characterisation of (the uncertainty of) the parameters and thus yields much more information than merely the mean and the spread that are obtained in a "classical" MLH-procedure. Skew confidence intervals for Θ can then be constructed on the basis of the quantiles of the ensemble $\left\{\hat{\Theta}^{(\ell)}\right\}_{\ell=1}^{L}$. For example, the lower limit of the 95% confidence interval is the 2.5% quantile, while the 97.5% quantile provides the upper bound of the 95% confidence interval.

On the basis of the parameters' distribution, the distribution of model's predictions can readily be computed, and in this way the uncertainty in a model's prediction. This uncertainty in a model's prediction can then also conveniently be represented by (for example 90 or 95%) confidence and/or prediction intervals.

For further explanation, and results of practical applications where Maximum Likelihood estimation procedures are applied to parameterised models for time series, and resampling techniques are used for the construction of skew confidence intervals, one is referred to Van den Boogaard et al. (2003, 2006).

In the present case the model's prediction intervals provide the desired means for testing the possible effect of an MV2 extension. In fact, the idea is to identify ("calibrate") the stochastic model of Equation 2.2.1 (with the right hand side extended with Equation 3 when long term trends must also be taken into account) on the basis of "only" t_0 measurements. The calibrated model is then applied in prediction mode for the times where t_1 measurements are available. In this way (e.g. 95%) prediction intervals are available and for each t_1 measurement it can then be verified whether or not it is contained in the corresponding prediction interval (NB. This is thus highly similar to the way Duin et al.

(2005a,b) verify whether or not remote sensing samples are statistically consistent with in situ data). In case a statistically significant fraction of the t_1 measurements is outside the prediction interval there is evidence of a systematic effect of MV2 on the SPM concentration at the location that is considered. Before to conclude this definitely, it must be checked carefully whether this discrepancy is merely due to significantly different external North Sea system conditions (meteorological, Rhine discharge, etc.) during the t_1 measurement(s) than during the t_0 measurement times.

B.3.2.2 Additional notes

1. The recipe described above can be applied separately for every spatial (horizontal and/or vertical) position where (in quantitative and qualitative sense) sufficient t_0 and t_1 SPM-measurements are available. Hereafter it can be verified for which positions significant MV2-effects are identified, and how these positions are geometrically clustered or distributed over the North Sea. Possibly this may lead to a finding that significant effects are "merely" limited to the vicinity of the Maasvlakte and/or positions in the Coastal River close to the coast.
2. Rather than using the measurements of single spatial positions, the procedure can be applied to spatially aggregated SPM measurements. The aggregation may consist of depth-averaged or depth-integrated SPM measurements. Alternatively aggregation may be carried out in the horizontal direction, and the averaging may be applied to the data of neighbouring measurement positions, or aggregation along a transverse coastal measurement section. More generally the averaging or integration may be in a form where the y_t in Equation B.1 represents an SPM-*flux* rather than a point wise concentration. An advantage of averaging is that noise in the data is reduced, which may improve the consistency and accuracy of estimates.
3. On the basis of the calibrated model, residuals can be computed. These residuals are defined as observed SPM values minus their model hindcast. By means of visualisation (plots of their temporal evolution and spatial distribution) and/or a quantitative analysis (computing statistics such as spreads, variances, extremes, root mean square, correlations, etc.) the properties of these residuals can be examined in further detail, with special attention for spatial dependencies and variations. This may for example give important insight in spatial length scales and temporal memory scales, and/or correlation with the system conditions during the measurements.

B.4 Multivariate methods for cross-shore transects

In this section the main issue is to use the SPM data of coastal transects to verify the effect of MV2 on the SPM distribution in the transversal direction in the "Coastal River". In particular this thus addresses hypothesized change I of section 2. This hypothesis suggests that an extension of MV2 may lead to redistribution of SPM in a direction orthogonal to the coast and in that case a spatial shift of t_1 data in the seaward direction is expected. The statistical measures and models formulated in this section may then be used to verify these assumptions in quantitative sense.

B.4.1 Evaluation and comparison of "elementary" statistics

Here similar statistical measures and time series analysis techniques can be used as listed in Section B.3.1. Cross-correlation functions can be mentioned as an additional procedure complementary to the auto-correlation functions mentioned in Section B.3.1. In fact, while auto-correlation functions deal with the analysis of one and the same times series (to identify temporal structures or components, and associated temporal memory scales), cross-correlation (or cross-covariance) functions can be applied to assess the similarity and/or mutual dependency of two different time series. In particular time lags between the two series can be obtained in this way, which can be used to compute velocities of the involved physical processes.

B.4.2 Model based identification of cross-shore magnitude of sediment concentrations or fluxes

Observed SPM concentrations at the various cross-shore transects in the North Sea show the largest concentrations near the coast which then decrease in the seaward direction. The idea is to formulate a parameterised model for this behaviour and identify this model on the basis of t_0 data. Uncertainties in the model and observations are represented by a spatial random noise. Observed data are used to calibrate this stochastic model for the transverse distribution of SPM. Together with the model's parameters, estimates for their uncertainty are also computed as for example 95% confidence and/or prediction intervals. In this way both in hindcast mode and in forecast mode uncertainties can be computed for the model's predictions. In particular it can then be verified whether or not t_1 SPM observations are statistically consistent with the transverse SPM distribution that is predicted by the model calibrated under t_0 conditions. In mathematical terms the model may have the following form:

$$c(y) = f(y \mid \Theta) + V_y \tag{B.4}$$

where,

y	The cross-shore spatial coordinate, for a certain section in the "Coastal River". At the coast *y*=0, while *y* increases in the seaward direction.
$c(y)$	SPM concentration at the transverse position *y*, and fixed coast longitudinal spatial coordinate *x* corresponding to the North Sea location of the section. Depending on the resolution of the observations, the dependency of the concentration on the vertical coordinate *z* must be considered separately, or the concentration *c*(*y*) must be taken as depth averaged or depth integrated values ($c(y) = \int c(y,z) \cdot dz$).
$f(\cdot \mid \Theta)$	A parameterised function that describes the deterministic long scale (systematic) spatial *y*-dependency of the concentration.
Θ	A set of parameters $\left(\Theta_1, \Theta_1, \cdots, \Theta_N\right)$ in the description of systematic variation of the SPM-concentrations in the transverse coastal direction.
V_y	A *spatial* random noise that accounts for the random fluctuations in the SPM concentration along the section.

Together with the model a set of observations $\left\{\hat{c}_m\right\}_{m=1}^{M}$ must be available that are used to identify the model's parameters, and statistical properties of the random noise V_y. These observations are assumed to be present for a sufficient number of positions y_m along the section. The $\hat{c}_m$ thus denotes the observed concentration at the coast transverse coordinate y_m, i.e. $\hat{c}_m := \hat{c}(y_m)$. On the basis of a visual inspection of $\left\{\hat{c}_m\right\}_{m=1}^{M}$ as function of the spatial coordinate y, a proper mathematical formulation for the function $f(\cdot\,|\,\Theta)$ must be defined. In case the concentrations tend to decrease in an exponential form along the coast transverse direction this $f(\cdot\,|\,\Theta)$ can for example be chosen as:

$$f(y\,|\,\Theta) = \Theta_1 \cdot \exp\left(-\Theta_2 \cdot y\right) \tag{B.5}$$

This function will be linear, $f(y\,|\,\Theta) = \Theta_1 + \Theta_2 \cdot y$, in case the model is defined/derived for the log transformed concentrations. Apart from the recipe of equation (B.5). many other alternative formulations may be possible. In fact $f(y\,|\,\Theta) = \Theta_1 / \left(1 + \left(\frac{y}{\Theta_2}\right)^{\Theta_3}\right)$ can be mentioned as another example for describing a monotonically decreasing behaviour, and in this case the model involves three unknown parameters.

The $\left\{\hat{c}_m\right\}_{m=1}^{M}$ data to calibrate the model (using again a Maximum Likelihood procedure to obtain "automatically" estimates for uncertainties for the model's parameters and model's predictions) must be selected appropriately. One may e.g. select all the observations of a particular season, and repeat the procedure for all seasons separately. In this way temporal dependencies in the model and its parameters can be verified. Alternative selection procedures may consist of considering "merely" extremes, or other data subsets confined to particular events. Similarly aggregated data samples may be considered as for example depth and/or time-averaged values.

Anyway the result will be that for each position y a prediction $c(y)$ is available together with a (e.g. 95%) confidence or prediction interval. For each t_1 observation it can then be verified whether or not this observation is covered by the t_0-based uncertainty interval. In case the MV2 extension indeed leads to a redistribution of SPM in the seaward direction it will have to be found that for positions close to the coast the t_1 samples are statistically significantly smaller than the t_0 mean (and/or even lower than the lower limit of the uncertainty interval), while sufficiently far away from the coast the opposite effect is found, i.e. t_1 samples are significantly larger than the t_0 mean, and/or exceed the upper limit of the uncertainty interval.

So far the modelling and analysis was assumed to be carried out for one particular observation section. Variations can be made with regard to the time domain for selecting or aggregating observed concentrations. In a next step the procedures can be repeated for all observation sections in the Coastal River with sufficient measurement data. By comparing the results of the various selection scenarios spatial (and/or temporal) dependencies of the model and its parameters can be verified, together with an assessment for which locations an extension of MV2 does or does not lead to significantly different redistributions of SPM in the coast transversal direction. This may give further insight in the spatial range, or spatial coverage, or length scales of an MV2 induced effect.

B.5 Multivariate methods for spatially distributed observations

In the preceding Sections the effect of an extension of MV2 was verified on the basis of statistical features and/or stochastic models for observed SPM concentrations of individual and/or spatially nearby locations as e.g. the measurement positions on a coast transverse section. In this section the relation between observed SPM-concentration of different and more remote spatial positions is considered. The intention is again to have a means to assess whether such system relations are affected by an extension of MV2. The spatial positions that are compared can be from any position in the North Sea where data is available, and in this way global (i.e. spatially distributed) effects of an extension of MV2 may be verified, if present and/or identifiable from the available measurement data.

B.5.1 Evaluation and comparison of "elementary" statistics

The evaluation of elementary statistics of observed SPM-data such as distribution functions, means, spreads, extremes, etc. and how these vary over the North Sea domain has more or less been addressed already in Section B.3.1. Here they are mentioned again as a method for obtaining a first impression of which locations, and/or system conditions, dependencies of SPM time series can be expected, and the length scales these dependencies involve. Such 'prior' information about mutual dependencies can facilitate the selection of the spatial positions that may be worthwhile to apply the system relation proposed below in Section B.5.2. With these system relations this mutual dependency and possible effect of MV2 is then assessed or verified in larger quantitative detail.
In the same way the auto- and particularly the cross-correlation functions (and/or spectral analysis techniques) mentioned above are an important additional means for a first assessment of mutual dependencies (and or similarity) of the SPM-time series of different positions. In particular time lags between the two series can be obtained in this way, which can be used to compute propagation velocities of the associated physical processes. These time lags and/or propagation times also provide useful information in the mathematical definition of system relations.
Similarly cross-correlation functions can be computed of SPM time series and time series of quantities that represent the external system conditions. These quantities are for example the discharge of the River Rhine, significant wave heights and current velocities at sea, wind speed and wind direction, or sea surface temperature. In this way mutual dependencies of SPM concentrations and the system conditions can be assessed. On this basis it can be verified which of these external system conditions must be taken into account in the construction of system relations as described in the next section.

B.5.2 System relations for SPM times series from different observation sites

In a system relation a time series $c(t,\vec{r}_1)$ of some physical process at a particular (spatial) position $\vec{r}_1$ is modelled as a function of this process (and/or other processes) at one or more other different positions $\vec{r}_2$. Usually this is done in the form of (linear or non-linear, parameterised) black box models which involve a number of unknown parameters. The

$c(t,\vec{r}_1)$ represents the model's output, while the $c(t,\vec{r}_2)$ of the other position(s) serve as input(s) of the model. Observed time series of the inputs and outputs must be used to identify the model's parameters. "Observed" data can be in the form of measured or observed data in the strict sense but can alternatively be predictions by a numerical model. In that case the system relation may serve as a reproduction function of the model which can for example be used for rapid assessment evaluations.
In the present case system relations will be based on observed SPM time series of different positions and they are used to identify quantitatively the mutual dependency. For the modelling of how the SPM-series of one position depends on that of another position, and/or external system conditions, (auto)regressive models (ARMAX-models, Autoregressive Moving Average models with or without eXternal input; see for example Chatfield, 1980, or Ljung and Söderström, 1983). In a formula such models may be of the form:

$$
\begin{aligned}
c_k^{(1)} = \quad & \alpha_0 \cdot c_k^{(2)} + \alpha_1 \cdot c_{k-1}^{(2)} + \alpha_2 \cdot c_{k-2}^{(2)} + \cdots \\
& \beta_0 \cdot U_k^{(1)} + \beta_1 \cdot U_{k-1}^{(1)} + \beta_2 \cdot U_{k-2}^{(1)} + \cdots \\
& \gamma_0 \cdot U_k^{(2)} + \gamma_1 \cdot U_{k-1}^{(2)} + \gamma_2 \cdot U_{k-2}^{(2)} + \cdots \\
& + \cdots + \\
& V_k
\end{aligned}
\tag{B.6}
$$

The model is defined in discrete time with $c_k^{(1)}$ the SPM-concentration $c(t,\vec{r}_1)$ at time $t=t_k$ with the t_k on an equidistant temporal grid: $t_k := t_0 + k \cdot \Delta t$ ($k = 0,1,2,3,\cdots$). The time step Δt is according to the sampling density of the measurements. The $c_t^{(1)}$ and $c_t^{(2)}$ are the SPM-time series of two different positions. The series $c_k^{(2)}$ are used as input in the model for the prediction of the 'first' series $c_k^{(1)}$ (the model's output). Apart from the $c_k^{(2)}$ other and/or more observed SPM series $c_t^{(3)}, c_t^{(4)}, \cdots$ may be used as input for the model. The $U_k^{(1)}, U_k^{(2)}, U_k^{(3)}, \cdots$ in equation (B.6) are also model inputs but these represent the external system conditions, or in other words the main external system forcing that are expected to affect the sediment transport in the North Sea. These external model inputs may for example be time series of the wind, flow currents, wave heights, or the sediment load from the Rhine-Muese estuary. These time series of the external forcing must be taken (if available) from one or more representative positions in the North Sea.

The $\alpha_i, \beta_j, \gamma_\ell, \cdots$ are uncertain model parameters in the deterministic part of the model. Note that in case of equation (B.6) this deterministic model is linear in its inputs (representing a linear transfer function from input to output). Non-linear generalisations (e.g. based on Neural Networks) of the transfer function are also possible but will involve much more unknown model parameters. In fact, this number of parameters can increase quite rapidly and soon be out of range when compared to the (presumably limited) amount of data for the model's input and output time series.

The V_k in equations (B.6) is a random noise and reflects the uncertainties and/or errors in the model. This noise need not to be white and neither stationary, and assumptions must be formulated or derived about its statistical properties. For this formulation of the model's uncertainty the same issues can be mentioned as discussed in before.

In applications the input series $c_k^{(2)}$ will usually be taken from an "upstream" position in the "Coastal River" while the series $c_k^{(1)}$ that one wants to model and/or predict are from "downstream" positions. Typically this may be in a form where (for example) the concentrations of the Egmond transect are predicted from those of the Noordwijk transect or locations even more close to the Maasvlakte, or further to the south.

Again the strategy is to use observed data of the input and output series to identify the parameters of the model together with estimates for their uncertainties. When this model calibration is based on t_0 data it can be applied in prediction mode on t_1 input data to obtain predictions of $c_k^{(1)}$ (and confidence and prediction intervals) for t_1 conditions. For t_1 measurements of $c_k^{(1)}$ it can then be verified whether or not these are covered by these confidence and prediction intervals, and in this way assess possible systematic ("statistically significant") effects induced by an MV2 extension.

B.6 Spatially distributed features in Remote Sensing Images

The hypotheses, and mathematical procedures for their verification, considered in preceding sections are to a large extent formulated for observations at "individual" spatial positions. For these "in situ" measurements it was assumed (more or less implicitly) that in temporal sense the sampling density is sufficiently high to represent the main temporal (longer term) variations and (short term) fluctuations. In this section a few notes are formulated on the use of Remote Sensing (RS) images which in contrast to in situ measurements provide high density spatially distributed information. This info extends over the whole North Sea area and is thus not merely restricted to near coast regions as is the case for most of the in situ measurements. Therefore RS-recordings have the advantage of providing detailed insight in (the evolution of) spatial patterns in the transport and spread of sediment. On the other hand, this spatial information is limited to the sea surface layer only, and at the same time the temporal density of such RS images is usually quite low due to cloud cover effects. Nevertheless on the basis of RS-images of SPM from before and after an extension of Maasvlakte evidence may become available for the (possible) effect of MV2 on spatial sediment transport patterns. It should be remarked here that the present interest is in the longer-term, few km-scale SPM distribution and not in individual SPM patterns e.g. due to eddies.

Because the regions of interest are (1) a relatively narrow (10 to 20 km) zone along the Dutch coast and (2) the Wadden Sea, the use of Remote Sensing may be limited. Inside the Wadden Sea remote sensing of SPM concentrations is technically not feasible because of drying of tidal flats and very shallow waters otherwise. The coastal zone is marked by a relatively strong cross-shore SPM gradient which can only be measured provide that land-sea masking, color saturation and shallowness of the water do not inhibit accurate measurements (see the report on data inventory).

We assume for the moment that it is feasible to obtain accurate near shore concentrations (i.e. with respect to offshore values) or other quantities (SST, for example). The remote sensing data may be combined with in situ data to obtain composite data sets. …

1. RS images may yield information on cross-shore gradients of SPM and SST. Methods similar to what is outlined in B.4 may then be suitable.
2. The line marking the y-location of the center of gravity of the pattern that stretches along the coast may be determined. This can be obtained after normalisation of the concentration field.
3. The along-shore line marking the 90 or 95% quantile (percentage of mass lying inshore of this line) can be determined as a measure for the width of the SPM distribution in the coastal river.

Test of MV2-effect on mean in SPM time series. Part I: Theory

In this section the assessment of a statistically/significantly different mean of SPM data before and after Maasvlakte 2 (MV2) is considered.

C.1 The Z-test for different means

The starting point is that for a certain fixed location a time series $\left\{c^{(-)}(t_k)\right\}_{k=1}^{K}$ of SPM-concentrations is available from before an extension of MV2, and a corresponding observed data set $\left\{c^{(+)}(s_\ell)\right\}_{\ell=1}^{L}$ after the MV2 extension. The Null-hypothesis about the means of two samples is that these are the same. To verify this assumption estimates $\overline{c}^{(-)}$ and $\overline{c}^{(+)}$ for these means are computed, and on the basis of the spreads $\overline{\sigma}^{(-)}$ and $\overline{\sigma}^{(+)}$ in these estimates for the means, it must be verified whether or not the means $\overline{c}^{(-)}$ and $\overline{c}^{(+)}$ are statistically consistent. In case that the number of observations before and after MV2 is sufficiently large (30 or more say, after correction for dependencies in the samples, see below) it may well be assumed that the random variables $\overline{c}^{(-)}$ and $\overline{c}^{(+)}$ satisfy a (log-)normal distribution, and the Z-test for difference in means can be applied. In that case the test statistic is:

$$Z = \frac{\overline{c}^{(+)} - \overline{c}^{(-)}}{\sqrt{\left(\overline{\sigma}^{(+)}\right)^2 + \left(\overline{\sigma}^{(-)}\right)^2}} \tag{C.1}$$

For a 95% confidence level, i.e. a significance level $\alpha = 0.05$, the critical values $z_{Cr}^{0.95}$ of Z are then -1.96 and 1.96 when considering a two sided test. Alternatively, in case of a 90% confidence interval ($\alpha = 0.10$) one will have $z_{Cr}^{0.9}$ =1.645.

C.2 Estimation of the means and their spreads

In this section it is outlined how to obtain estimates for the means $\overline{c}^{(-)}$ and $\overline{c}^{(+)}$, and spreads $\overline{\sigma}^{(-)}$ and $\overline{\sigma}^{(+)}$, that can be substituted in the right hand side of Equation C.1 in order to evaluate and test the *Z*-statistic. Assuming that the time series $\left\{c^{(-)}(t_k)\right\}_{k=1}^{K}$ (before MV2) and $\left\{c^{(+)}(s_\ell)\right\}_{\ell=1}^{L}$ (after the MV2) are independent, the recipe for the estimation of $\{\overline{c}^{(-)},\ \overline{\sigma}^{(-)}\}$ is the same as for $\{\overline{c}^{(+)},\ \overline{\sigma}^{(+)}\}$. Quite generally we must thus solve the problem how to compute the mean from some "arbitrary" time series $\left\{X(t_k)\right\}_{k=1}^{K}$, together with the spread that must be assigned to the estimate for the mean.

In the special case that the data points $\{X(t_k)\}_{k=1}^{K}$ are *independent*, and identically distributed the (estimate for the) mean $\overline{x}$ and its spread $s_{\overline{x}}$ follow from:

$$\begin{cases} \overline{x} := \frac{1}{K} \cdot \sum_{k=1}^{K} X(t_k) \\ s_{\overline{x}} := \dfrac{s_X}{\sqrt{K}} \end{cases} \tag{C.2a}$$

The s_X in this expression is the (estimate of the) spread of the $X(t_k)$ and can be computed according to:

$$s_X := \sqrt{\tfrac{1}{K-1} \cdot \sum_{k=1}^{K} \left(X(t_k) - \overline{x} \right)^2} \tag{C.2b}$$

As a result:

$$s_{\overline{x}} := \sqrt{\tfrac{1}{K \cdot (K-1)} \cdot \sum_{k=1}^{K} \left(X(t_k) - \overline{x} \right)^2} \approx \tfrac{1}{K} \cdot \sqrt{\sum_{k=1}^{K} \left(X(t_k) - \overline{x} \right)^2} \tag{C.2c}$$

For an observed set of SPM-concentrations the data points can be mutually correlated, however, and as a result the $\{X(t_k)\}_{k=1}^{K}$ cannot always be treated as independent observations. The main issue is then how to deal with these dependencies, and obtain the properly modified expressions for the right hand sides in Equation C.2. Here we will follow a Maximum Likelihood approach and treat the data set $\{X(t_k)\}_{k=1}^{K}$ as observations of a continuous time stochastic process $X(\cdot)$ of the form:

$$X(t) = \alpha_0 + V(t) \tag{C.3}$$

The $V(\cdot)$ is assumed be a zero-mean random process with auto-covariance function $\gamma(\cdot,\cdot)$ where $\gamma(s,t) := \mathrm{E}\left[V(s) \cdot V(t)\right]$. It must be noted that $V(\cdot)$ need not to be a white process, and neither stationary. In particular it is then dealt with a possible heteroskedastic behaviour of the SPM-processes (i.e. variations and uncertainties that are time dependent).
Through the auto-covariance function $\gamma(\cdot,\cdot)$ mutual dependencies in the measurements $\{X(t_k)\}_{k=1}^{K}$ of $X(\cdot)$ are taken into account as well. In fact, the covariance of the data points $X(t_k)$ and $X(t_\ell)$ is given by $\Gamma_{k,\ell} := \gamma(t_k, t_\ell)$, and the $\Gamma_{k,\ell}$ are the entries of a $K \times K$ symmetric covariance matrix Γ. The inverse of this matrix will be denoted by Γ^{-1}.

It can then be shown that the Maximum Likelihood estimate $\hat{\alpha}_0$ of the mean α_0 is given by:

$$\hat{\alpha}_0 = \frac{\sum_{k,\ell=1}^{K} \left(\Gamma^{-1}\right)_{k,\ell} \cdot X(t_\ell)}{\sum_{k,\ell=1}^{K} \left(\Gamma^{-1}\right)_{k,\ell}} \tag{C.4a}$$

and the *variance* and spread of this estimate for the mean are:

$$VAR\left[\hat{\alpha}_0\right] = \frac{1}{\sum_{k,\ell=1}^{K} \left(\Gamma^{-1}\right)_{k,\ell}} \quad , \quad SPREAD\left[\hat{\alpha}_0\right] = \frac{1}{\sqrt{\sum_{k,\ell=1}^{K} \left(\Gamma^{-1}\right)_{k,\ell}}} \tag{C.4b}$$

For a more convenient understanding of these expression we consider the *special case* that the uncertainties in the measurements are *independent* but still with different spread (with σ_k the spread of $X(t_k)$). In that case we have $\Gamma_{k,k} = \sigma_k^2$, and $\Gamma_{k,\ell} = 0$ for $k \neq \ell$, and for the estimate of the mean and its variance and spread this will lead to:

$$\hat{\alpha}_0 = \frac{\sum_{k=1}^{K} \frac{1}{\sigma_k^2} \cdot X(t_k)}{\sum_{k=1}^{K} \frac{1}{\sigma_k^2}} \quad , \quad VAR\left[\,\hat{\alpha}_0\right] = \frac{1}{\sum_{k=1}^{K} \frac{1}{\sigma_k^2}} \quad , \quad SPREAD\left[\,\hat{\alpha}_0\right] = \frac{1}{\sqrt{\sum_{k=1}^{K} \frac{1}{\sigma_k^2}}} \tag{C.5}$$

A further "simplification" can be derived when all the spreads are identical, i.e. $\sigma_k = \sigma$ for all $k\,(1 \leq k \leq K)$. In that case:

$$\hat{\alpha}_0 = \tfrac{1}{K} \cdot \sum_{k=1}^{K} X(t_k) \quad , \quad VAR\left[\,\hat{\alpha}_0\right] = \frac{\sigma^2}{K} \, , \quad SPREAD\left[\,\hat{\alpha}_0\right] = \frac{\sigma}{\sqrt{K}} \tag{C.6}$$

It is readily verified that Equation C.6 corresponds to the formulations for the mean and its spread that were given at the begin of this section for the case of *independent* and identically distributed data points $\left\{X(t_k)\right\}_{k=1}^{K}$. See the Equations C.3 with $\overline{x} \leftrightarrow \alpha_0$ and $s_X \leftrightarrow \sigma$.

In summary we may then conclude that in case of mutual dependencies in the SPM measurements $\left\{X(t_k)\right\}_{k=1}^{K}$ the desired mean of the SPM data series and its spread can be computed on the basis of Equations C.4. A proper formulation must yet be obtained for the auto-covariance function $\gamma(\cdot,\cdot)$. In practice an exponential form is often chosen for $\gamma(\cdot,\cdot)$. For a stationary random process this gives:

$$\gamma(t_k, t_\ell) = \sigma^2 \cdot \exp\left(-\frac{\left|t_k - t_\ell\right|}{\tau_{AC}}\right) \tag{C.7}$$

The σ is the spread of the random process, and the τ_{AC} is an auto-correlation time. The $\gamma(\cdot,\cdot)$ of Equation C.7 can appropriately be generalised to a version for non-stationary and heteroskedastic random processes. For convenience this generalisation is here not further considered, but left as an issue for future investigation.

The auto-correlation function illustrated in Figure 8.2.3 shows that the assumption of an exponential $\gamma(\cdot,\cdot)$ is reasonably well satisfied by the SPM-measurements of Noordwijk 20. For the Noordwijk 02 series this tends to be the case as well, at least when the series are corrected for a seasonal periodic component, see Figure 8.2.2.
Apart from these practical justifications there is also an important "theoretical" advantage of an exponential auto-covariance function. In fact for a covariance matrix Γ with entries $\Gamma_{k,\ell} := \gamma(t_k, t_\ell) = \sigma^2 \cdot \exp\left(-\frac{|t_k - t_\ell|}{\tau_{AC}}\right)$ the inverse Γ^{-1} can be determined analytically. As a result the $\hat{\alpha}_0$ of Equation C.4*a*, and its spread as prescribed by Equation C.4*b*, can both be computed analytically. Here we give the expressions in case that the observations $\{X(t_k)\}_{k=1}^{K}$ are on an equidistant temporal grid, i.e. $t_k = t_0 + k \cdot \Delta t$:

$$\hat{\alpha}_0 = \frac{\frac{X(t_1)}{1-\beta} + \sum_{k=2}^{K-1} X(t_k) + \frac{X(t_K)}{1-\beta}}{K + \frac{2\cdot\beta}{1-\beta}} \qquad \text{(C.8a)}$$

$$VAR\left[\hat{\alpha}_0\right] = \frac{\sigma^2}{\frac{1-\beta}{1+\beta}\cdot K + \frac{2\cdot\beta}{1+\beta}} \qquad \text{(C.8b)}$$

$$SPREAD\left[\hat{\alpha}_0\right] = \frac{\sigma}{\sqrt{\frac{1-\beta}{1+\beta}\cdot K + \frac{2\cdot\beta}{1+\beta}}} \qquad \text{(C.8c)}$$

where:

$$\beta := \exp\left(-\frac{\Delta t}{\tau_{AC}}\right) \qquad \text{(C.8d)}$$

As a matter of its definition the β (with $0 \le \beta < 1$) then represents the *correlation coefficient* of neighbouring observations, and is thus a convenient measure for dependencies in the measurement set. Note that for $\beta = 0$ (all measurements are mutually independent) the right hand sides of the Equations C.8*abc* are fully consistent with those of C.6 and C.3.

For a large number of samples (*K*>50, say) the expression for the mean (in the right hand side of Equation C.8a) will hardly be different from the standard mean of the samples. For the spread as expressed by the right hand side of Equation C.8c a suitable approximation will be:

$$SPREAD\left[\hat{\alpha}_0\right] = \frac{\sigma}{\sqrt{\frac{1-\beta}{1+\beta}\cdot K}} \qquad \text{(C.9)}$$

This expression allows an important conclusion, in the sense that in case of mutual dependencies in the measurement the "effective number of observations" is $K_{Eff} = \dfrac{1-\beta}{1+\beta} \cdot K$, and this K_{Eff} may be significantly less than K, the actual number of observations. For example, in case $\beta = \exp\left(-\frac{\Delta t}{\tau_{AC}}\right) = 0.9$ one will have $K_{Eff} = \frac{1}{19} \cdot K$ so that hardly more accuracy in the estimate of the mean is obtained as when 19 time fewer samples were recorded (and/but with a 19 times larger sampling interval Δt to cover the same measurement period).

Therefore a small sampling interval Δt ($\frac{\Delta t}{\tau_{AC}} < 1$, say) does not make much sense for accurate *assessments of the mean* of the SPM series. It must be noted, however, that for *other statistics* a small sampling interval Δt ($\frac{\Delta t}{\tau_{AC}} << 1$) can be essential. This will be the case, for example, when estimates for the auto-correlation time τ_{AC} (or time scales of short term sub-processes) of the SPM-process are required.