Project no. 265863

ACCESS

Arctic Climate Change, Economy and Society

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Thematic Priority:	Ocean.2010-1 “Quantification of climate change impacts on economic sectors in the Arctic”

D1.11 – Report on successful test of quantitative network design framework

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Dissemination Level		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

1) Executive Summary

Task 1.1 developed a framework for a modelling system to assist the design quantitative design of the Arctic Observing System. The Arctic Observational Network Design (AOND) system was developed around the advanced data assimilation system NAOSIMDAS which uses, in its core, a model of the coupled Arctic sea-ice ocean system. The AOND system can evaluate candidate observational networks in terms of their constraint on target quantities of interest, e.g. predicted ice area or volume for a given region. As a demonstration of its functionality, we apply the system to evaluate a hypothetical space mission observing ice area.

2) Introduction

For an offshore platform, information about the ice conditions expected for the next few days in its vicinity is crucial. Similarly, for shipping companies, a forecast of the ice conditions along, say, the Northern sea route is clearly desirable. If we replace 'ice conditions' by 'ice thickness', these are just two examples of physical quantities of interest, which are not observable. In this case, this is because these *target quantities* refer to a period in the future. In other cases, the target quantity may not be accessible through direct measurements. For example, we cannot directly measure the ice export through Fram Strait or the mean temperature of the Arctic ocean. We can, however, simulate all the above examples of target quantities with a numerical model of the Arctic ocean sea-ice system such as NAOSIM (Kauker et al., 2003).

A drawback of such model simulations is that they are uncertain for a number of reasons. Among these reasons are uncertainties in input quantities to the simulation, such as the state at the beginning of the simulation (initial state) and the atmospheric boundary condition over the simulation period. Also, there are uncertain constants in the formulation of the model equations (process parameters). Observations of the ocean sea-ice system have the potential to reduce this uncertainty. Variational Data Assimilation systems systematically combine observational information with numerical models and prior information on a control vector that is composed by a combination of and the above quantities (initial and boundary conditions and process parameters). An example is NAOSIMDAS, a variational assimilation system constructed around NAOSIM, which has been applied to prediction of the Arctic ice concentration on seasonal time scale (Kauker et al., 2010). Another example, is Arctic version (Heimbach et al., 2010) of the ocean state estimation system of the *Estimating the Circulation and Climate of the Ocean* (ECCO) project.

3) Methodology

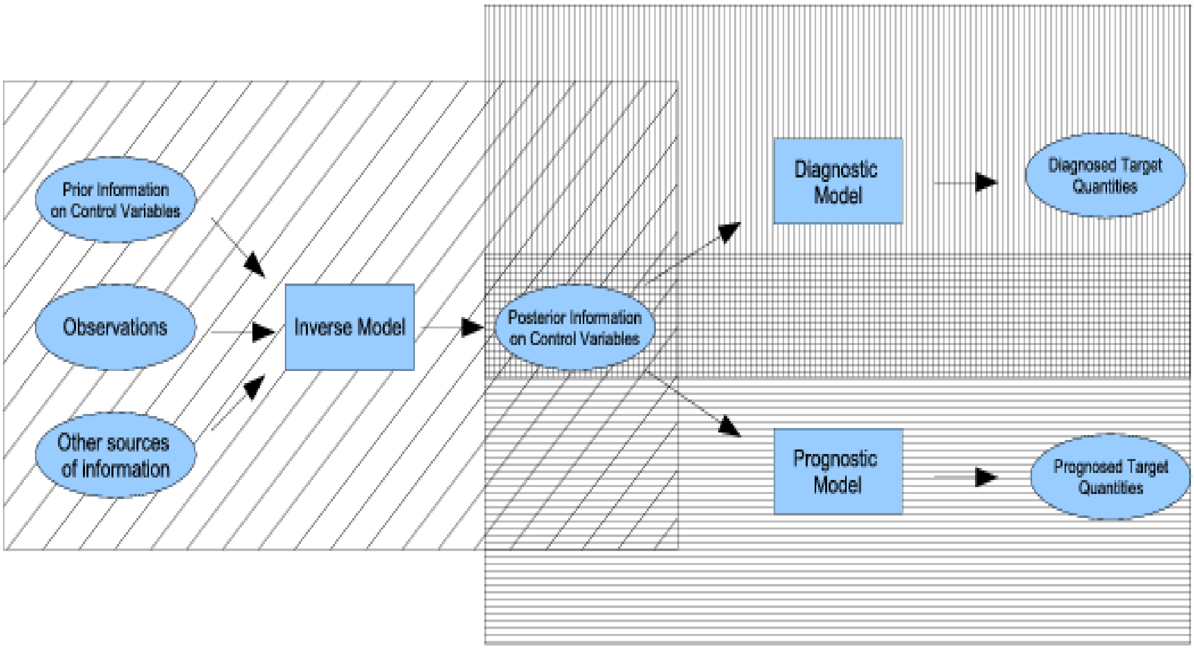

Figure 1: Flow of information through an advanced assimilation/inversion system (adapted from Scholze et al., 2007).

Advanced data assimilation systems are also capable of inferring *posterior* uncertainty ranges of the control vector (composed of initial and boundary conditions and process parameters) such that they are consistent with the *data uncertainty*, i.e. the uncertainty ranges associated with the observations (Figure 1). The data uncertainy is the combination of observational and model uncertainty, the latter reflecting residual imperfections in the model that cannot be resolved by optimising the control vector (Tarantola, 1997). In a second step these posterior uncertainty ranges can then be mapped forward onto uncertainty ranges in a target quantity. Doing this uncertainty propagation twice, with and without observations, quantifies the added value through the observations in terms of an uncertainty reduction in the target quantity. For an example expressing the added value of atmospheric carbon dioxide observations for constraining net and gross carbon fluxes simulated by a terrestrial biosphere model see Rayner et al., 2005.

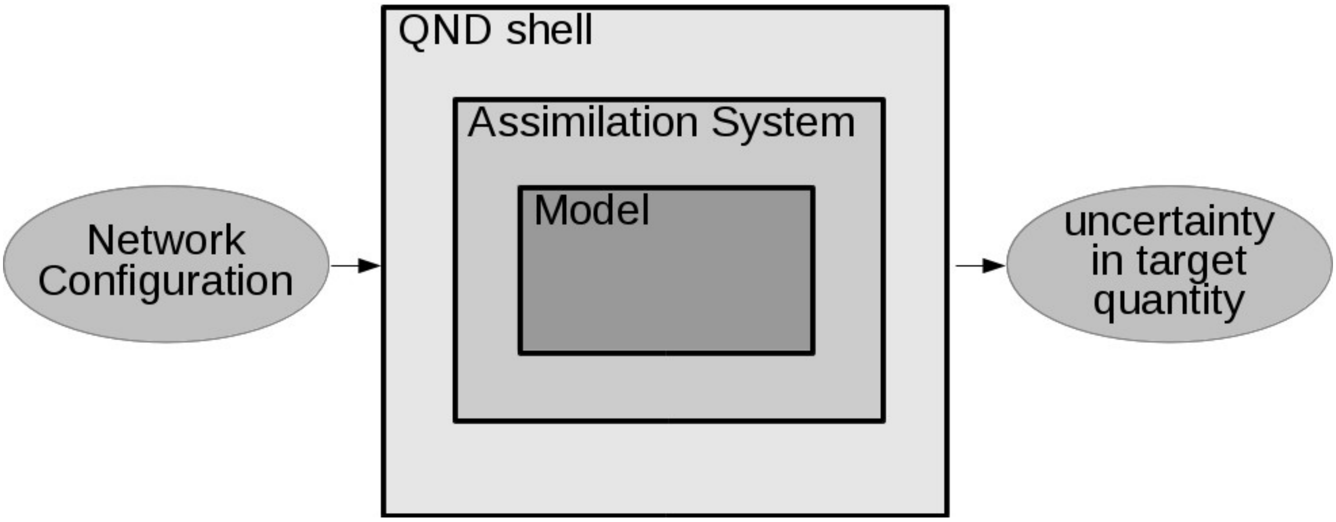

Figure 2: Schematic Presentation of Quantitative Network Design Procedure. Network configuration includes samples quantities, sampling times and locations and data uncertainty.

Quantitative Network Design (QND) systems exploit this capability of uncertainty propagation. They are built around assimilation systems (Figure 2) and calculate posterior uncertainty ranges in one or several target quantities that are consistent with data uncertainties in given observational networks. The methodology (see Kaminski and Rayner, 2008) can also be applied to hypothetical observations, provided that (1) they can be simulated with the model and (2) the data uncertainty can be estimated. A QND system is, hence, capable of assessing the performance of a set of candidate networks, as quantified by the uncertainty in a set of target quantities. This means we can use a QND system to construct network configurations that meet the requirements of stakeholders such as shipping companies or offshore platforms. The technique is successfully applied in other areas of environmental science, e.g. to networks observing the global carbon cycle: Kaminski et al. (2010) applied QND to evaluate a mission concept for observing atmospheric carbon dioxide from space. An interactive QND system (publicly available at http://imecc.ccdas.org) for atmospheric and terrestrial observations constraining the terrestrial carbon fluxes was set up and applied by Kaminski et al. (2012).

An AOND system was built around NAOSIM by FastOpt and OASys. The model domain extends from the Arctic to the North Atlantic north of 50 degrees North on a 2 by 2 degree grid, where the pole is rotated to the equator (Figure 3). It is set up for a simulation period covering January 2007 and uses a seven dimensional control vector composed of scalar multipliers for the initial ocean temperature, the atmospheric temperature, and the zonal wind stress component as well as two parameters of the ocean component and two of the sea-ice component. As target quantities it offers Arctic-wide average values of the ocean kinetic energy, the ocean temperature and salinity as well as the total ice volume and area. The QND system allows to test networks composed of daily samples of up to three data streams. These data streams are ice concentration and thickness as well as snow thickness, available over the entire model domain. The respective data uncertainties and the number of daily samples are flexible.

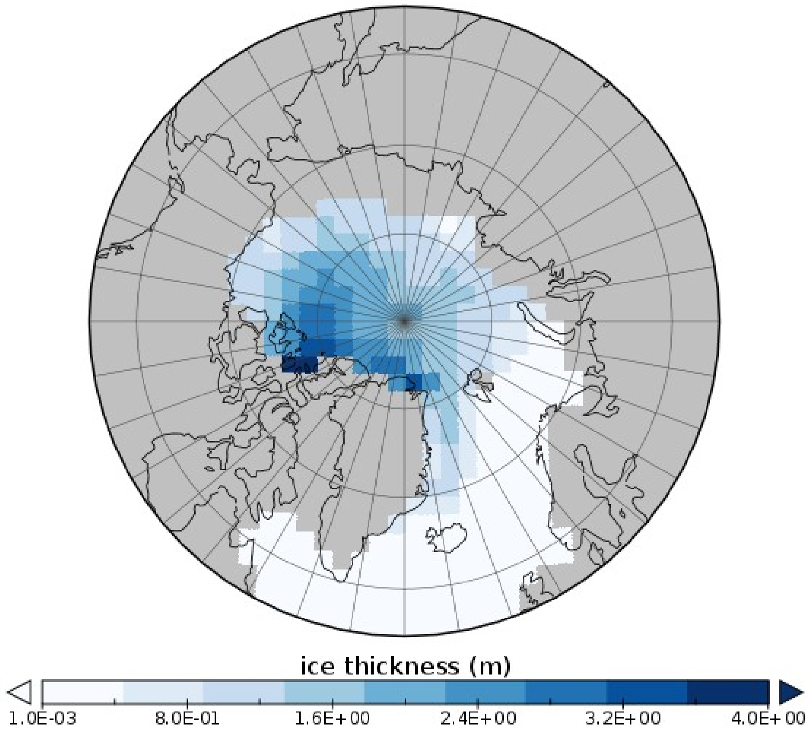

Figure 3: Model domain. Southern boundary is 50 degrees North.

4) Application

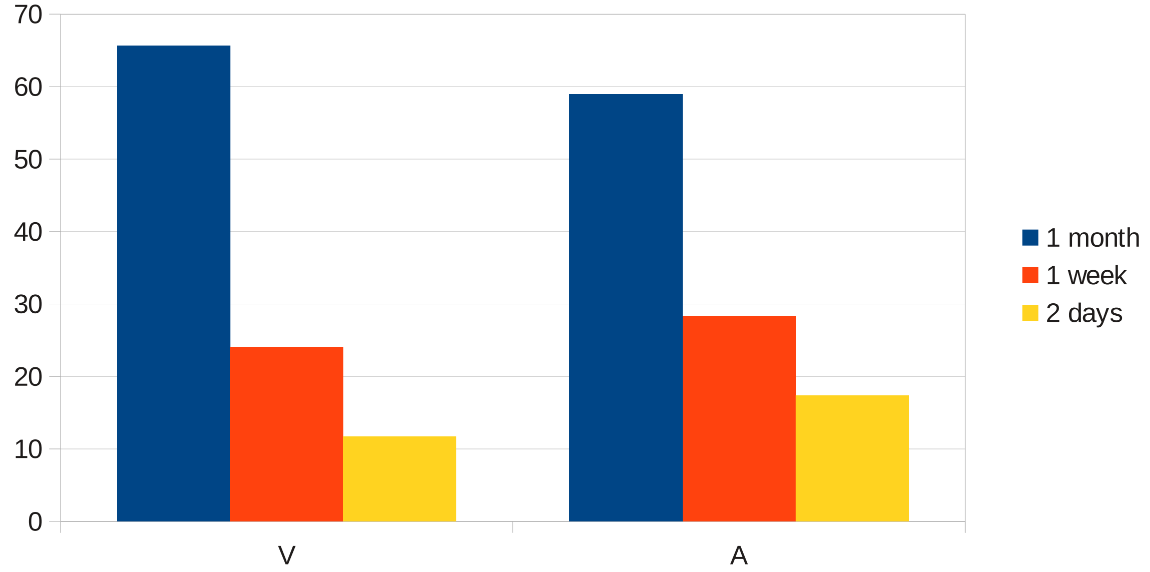

Figure 4: Uncertainty Reduction in % for total ice volume (V) and total ice area (A) averaged over January 2007 and model domain for daily samples of ice concentration over every grid cell at every day (blue), the first seven days (red) and the first two days in January.

As an application example of the AOND system, Figure 4 displays an evaluation of three networks sampling ice concentration with ice volume and area as target quantities. All networks sample every grid cell in the entire model domain with a data uncertainty of 20%, but they differ in the number of daily samples. The first network (blue bars) samples every day in January, while the second (orange bars) samples only the first week and the third (yellow bars) only the first two days. The quantity displayed is uncertainty reduction in the target quantities, relative to the prior uncertainty i.e. a case without any observations. For example, an uncertainty reduction value of 0% means the observations do not reduce any uncertainty, while a value of 50% means the posterior uncertainty is half of the prior uncertainty. We can note at least two points: First, even though we are observing ice concentration, in one out of three cases (every day sampling) the uncertainty reduction for ice volume is higher than for ice area. This may happen, because any uncertainty reduction in the area will, hence, also show up in the volume. On top, the volume is affected by uncertainty reduction in the thickness, which, through the dynamics of the model, is linked to ice concentration. Whether the uncertainty reduction on ice volume can actually exceed the effect on ice area depends on the relative contribution of ice volume and area on a grid cell level to the totals. If a grid cell exhibits a large ice covered area of very thin ice, reducing the uncertainy on the ice area will have a larger contribution on the uncertainty reduction for the total ice area than for the total ice volume. The second point to note is that the shorter the observed period the higher the posterior uncertainty. Revisiting our initial examples, we note that, unfortunately, forecasted ice thickness around a platform or a shipping route, is more similar to the 1 week or the 2 day case, where (most of) the target quantity extends into the future. By contrast, retrospective analyses of the Arctic system use a setup similar to the 1 month case.

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