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Development of methods to assimilate satellite observations to operative environmental monitoring and forecasting system of Finland

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ABSTRACT: Novel methods are developed to directly assimilate remote sensing data to (a) discrete *in situ* monitoring data and (b) environmental models. The objective is to investigate the feasibility of the developed methods as they are applied to the operative and semi-operative systems employed in Finland by the Finnish Environment Institute. The development work is focused on (a) water quality monitoring and prediction and (b) hydrological monitoring and forecasting. The investigated applications include the monitoring and prediction of snowmelt, runoff and the level of soil moisture/evapotranspiration. The developed assimilation procedures take into account the accuracy characteristics of physical models (or those of *in situ* data), the accuracy of remote sensing data and models, and additionally, the propagation of errors with time. The first test results of satellite data assimilation to dynamical environmental models were obtained in snowmelt monitoring/discharge forecasting. These results indicate that the inclusion of satellite data improves the performance of run-off forecasting models during the critical snow melt period. As well, encouraging results were obtained in the in the case of snow depth mapping when assimilating remote sensing data to discrete *in situ* observations (to snow depth values interpolated from discrete observation data).

1 INTRODUCTION

The assimilation of remote sensing data to aquatic and terrestrial environmental models is a new topic, the status of which is mainly in the level of basic research. First suggestions and test results have been reported for such applications as: (a) retrieval of snow water equivalent using space-borne microwave radiometer data combined with hydrological snow models (Wilson et al., 1999), (b) soil moisture and temperature monitoring in non-forested areas using the assimilation of hydrological model predictions and microwave remote sensing data (Houser et al., 1998), and (c) coupling of a hydrodynamic ecosystem model with optical satellite data for investigating the phytoplankton dynamics in a coastal ecosystem (Semovski et al., 1999). Semi-operative systems have been tested for few applications. They include the monitoring of suspended matter in coastal areas by assimilating remote sensing data to water quality models (Vos et al., 1998). The assimilation methods proposed and tested up-to-date are relatively simple approaches that include deficiencies. Typically, they do not properly consider the stochastic error characteristics of physical models and remote sensing observations, or they are restricted to the use of linear assimilation methods.

Our research is focused on (1) water quality monitoring and (2) hydrological modeling and forecasting. The objective is to develop a novel methodology to assimilate remote sensing data to dynamic environmental models. The specific applications include (a) water quality monitoring and prediction in lake areas and (b) hydrological monitoring and forecasting, including snow melt and runoff/discharge monitoring, and additionally, estimation of soil moisture and evapotransipiration under summer conditions.

The methods are developed and tested for Finnish conditions (and the Baltic Sea) using available optical and microwave satellite data, such as NOAA AVHRR, ERS-2 SAR and MODIS spectrometer observations. However, part of the methodology development and testing work has been carried out using other available data sets, including passive SSM/I microwave radiometer observations covering the northern parts of Eurasia.

2 ASSIMILATION METHODOLOGY

The developed assimilation techniques take into account the accuracy characteristics of physical models - or those of interpolated *in situ*. Also, the statistical accuracy characteristics of remote sensing data and remote sensing models and the propagation of errors with time are simultaneously considered. The tested algorithms include an approach in which both the physical/conceptual environmental model and the remote sensing model are optimized by applying a constrained iterative algorithm in which the difference between the remote sensing model and remote sensing observations is minimized by optimizing the value of an uncertain physical model state variable(s) (statistical inversion using a maximum *a posteriori* likelihood method), refer to Fig. 1.

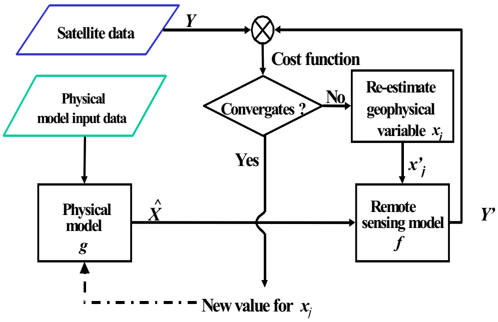

Figure 1. A general flow chart of data assimilation system. The physical dynamic environmental model *g* is linked to satellite data through a remote sensing model *f* (a forward model that describes the satellite observations as a function of physical model state variables *X*). The optimum value(s) of state variable(s) is/are searched by finding a global minimum of a cost function that includes the squared difference of (multi-channel) satellite observations and simulated satellite observations $(Y – Y')^2$.

2.1 *Practical implementation of method in case of hydrological forecasting*

The developed assimilation method is implemented according to principle presented in Fig. 1. In practice, the hydrological model is optimized with respect to a certain model state variable(s) by searching iteratively a global minimum of a specific cost function. The cost function takes into account (a) the squared difference of remote sensing model predictions and remote sensing observations and (b) the squared difference of the iteratively adjusted and the originally determined value of the state variable(s). These both terms are weighed with the statistical accuracy of remote sensing model predictions and that of the hydrological model predictions, respectively.

The application investigated here is the assimilation of remote sensing data to an operative hydrological model during the spring melt period. The particular model state variable adjusted in the assimilation is the Snow Covered Area (SCA), as both optical and microwave radar satellite observations are highly sensitive to changes in SCA, also in boreal forest zone (Metsämäki et al., 2001).

2.2 *Method combining remote sensing data with interpolated observation data*

In this case, an estimate for the value of a certain geophysical variable for a given location is first interpolated from discrete observations. In the second step, that value is used as an *a priori* estimate when a remote sensing model is fitted to space-borne observations by optimizing the value of the geophysical variable. In the fitting procedure, the *a priori* value of the variable is weighed with its modeled statistical uncertainty, which is estimated using spatial data analysis techniques (kriging interpolation). As well, the remote sensing data is weighed with the estimated accuracy of remote sensing data modeling. In that case, weighing factors are determined by analyzing how well the remote sensing model describes the observations at the locations of discrete data points for the day under investigation

3 STUDY AREAS, MODELS AND DATA

The main test areas are the River Kemijoki drainage area, northern Finland (snow hydrology applications), Lake Längelmävesi, southern Finland (water quality applications) and Siuntio test site (soil moisture and evapotranspiration applications). Additionally, the whole northern Eurasia is used as a test site in testing the developed assimilation techniques for snow depth mapping. As well, the Gulf of Finland and the Finnish coastal areas are used as additional test sites in investigations concerning water quality prediction. In this paper we concentrate on presenting first results obtained for the River Kemijoki area and northern Eurasia. Hence, data and models dealing with these two regions are discussed next in more detail.

3.1 *Snow hydrology applications*

The testing of assimilation techniques for snow melt and runoff prediction applications is carried out for a sub-region of the river Kemijoki drainage area (northern Finland), see Fig. 2. The hydrological model tested is the operational WSFS (Watershed Forecasting and Simulation) model of the Finnish Environment Institute. The same model is used to forecast the discharge of all major rivers of

Finland. The model input data includes several interpolated meteorological variables, such as temperature and precipitation.

Figure 2. Assimilation methodology test site near the Lake Lokka, northern Finland. The sub-darinage areas employed by the WSFS model are also shown. The test site covers a small section of the River Kemijoki drainage area. The width of the depicted area is 60 km.

The satellite data tested up-to-date consists of a total of 16 ERS 2-satellite C-band SAR images from the years 1997, 1998, 2000, and 2001 (spring melt season for each year). The backscattering values from 14 small sub-drainage areas (calculation units of the hydrological model shown in Fig. 1) are classified into five classes based on forest stem volume information available through digital land use data. The averaged backscattering coefficient values of different classes (from each sub-drainage area) are employed in the actual data assimilation procedure.

The employed remote sensing model is based on the semi-empirical HUT forest backscattering model (Pulliainen et al., 1999a), which describes the average backscattering coefficient of forested terrain as a function of forest stem volume (biomass). The effect of snow cover is included in the modelling approach empirically by applying reference images that represent both totally wet snow covered conditions and snow-free conditions. As an outcome, the model predicts the radar-observed backscattering coefficient as a function of Snow Covered Area (SCA) and forest stem volume. Additionally, the model takes into account the temporal, weather dependent, changes of forest canopy backscatter, which is essential regarding SCA estimation performance (Pulliainen et al., 2001).

3.2 *Snow depth mapping applications*

The testing of an algorithm that assimilates remote sensing data to interpolated *in situ* data was carried out for 22 stations around the Northwestern Russia and Siberia for the winter of 1993/94. The reference data consisted of daily *in situ* snow depth observations from weather stations. These data were available through NSIDC/University of Colorado (Armstrong, 2001). All the stations are located in the boreal forest or sub-arctic zone of Eurasia. Observations from test stations were used for determining the interpolated reference snow depth masks in data assimilation algorithm testing. The algorithm testing was carried out using daily averaged SSM/I brightness temperature observations (Maslanik and Stroave, 1990) from 22 fixed grid cells around each station, each cell having a size of 25 km by 25 km.

The brightness temperature model employed in the data assimilation is the semi-empirical, radiative transfer approach-based HUT Snow Emission Model (Pulliainen et al., 1999b).

4 RESULTS

4.1 *Discharge forecasting and SCA estimation during the snow melt period*

The accuracy improvement of both the discharge forecasting and SCA estimation is preliminarily tested for the River Kemijoki test site using ERS-2 SAR data. For the validation of results several reference data sets were available: Discharge measurements, SCA estimations from optical satellite images, and weather station observations on temperature, daily SCA and daily snow depth value.

The WSFS model has two correction factors that can be adjusted historically: temperature and precipitation correction factors. These both factors have a direct effect on SCA during the spring melt period. Increasing the temperature accelerates the melting process (if done during the melting season) or shifts the beginning of the melting earlier. In the other hand, increasing the precipitation (if done before the melting season) increases the snow depth and the volume of the discharge. In practice, the assimilation procedure adjusts either of these two parameters instead of SCA. These parameters can be used to drift the internal model state variable SCA to the direction that the satellite observations points. The output of the model (discharge) behaves though quite differently in these cases.

An example of assimilation results is shown in Fig. 3. In this case, assimilating a single SAR image into the WSFS model optimised the precipitation correction coefficient. Fig. 3 depicts the discharge prediction of the WSFS model obtained using this adjusted precipitation correction coefficient. The original WSFS discharge forecast and the independently measured discharge are also shown for comparison. Additionally, Fig. 3 presents the original SCA prediction together with the SCA prediction calculated using the adjusted precipitation correction coefficient.

Another example on assimilation performance is depicted in Fig. 4. In this case the temperature correction factor is adjusted in the assimilation procedure. Again, the discharge forecasts obtained with and without data assimilation are depicted, as well as the corresponding SCA predictions. The observed true discharge is also shown

The test results indicate that the inclusion of the satellite data improves the performance of the discharge forecast model during the snowmelt period. However, difficulties arise due to the prefixed parametrisation of hydrological models. The results indicate that the optimum assimilation performance is obtained when the regional parametrisation is changed based on remote sensing data.

4.2 *Snow depth estimation through the assimilation of radiometer observations to interpolated in situ observation data*

The assimilation algorithm testing was carried out using altogether 3300 data points from 22 stations representing a five-month period. The performance characteristics were determined for each station, one by one, by assuming that the Snow Depth (SD) values for that station are unknown while they are known for the other 21 stations. The results indicate that the use of SSM/I data, in addition to ground-based observations, improves the SD estimation accuracy in 62% of the investigated 3300 cases. Further on, the magnitudes of improvements were higher than the magnitudes of observed deteriorations (i.e. cases where data assimilation shifted SD estimates towards the wrong direction). Altogether, data assimilation appeared to perform well for 20 test stations out of the total of 22 stations. An example of assimilation results for a single test station is shown in Fig. 5, and the histogram on accuracy improvement obtained for 22 test stations is presented in Fig. 6.

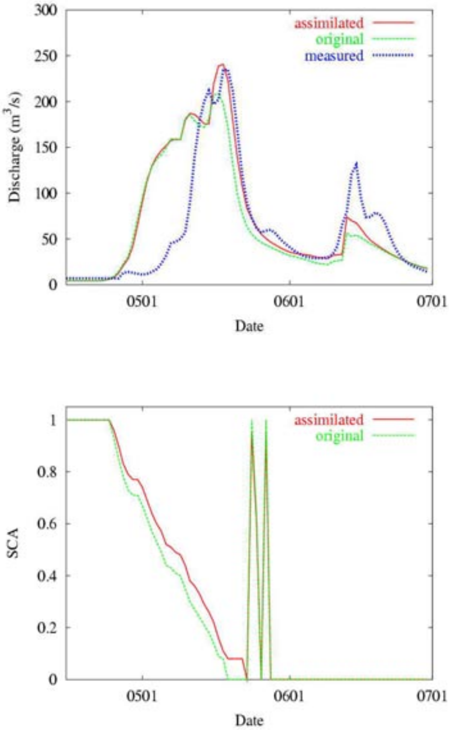

Figure 3. Measured (observed) discharge, discharge from the WSFS model without (original) and with the precipitation correction obtained through the assimilation procedure, and corresponding SCA predictions for spring 1998. The ERS-2 SAR image used for the assimilation is acquired for 13 May 1998.

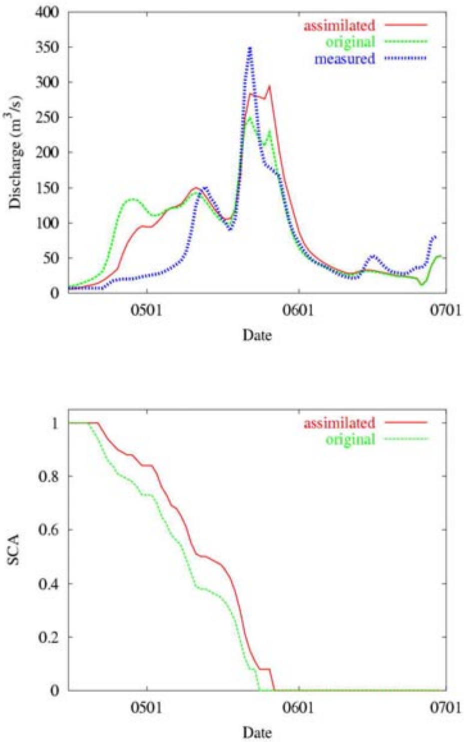

Figure 4. Measured (observed) discharge, discharge from the WSFS model without (original) and with the temperature correction obtained through the assimilation procedure, and corresponding SCA predictions for spring 2000. The ERS-2 SAR image used for the assimilation is acquired for 24 May 2000.

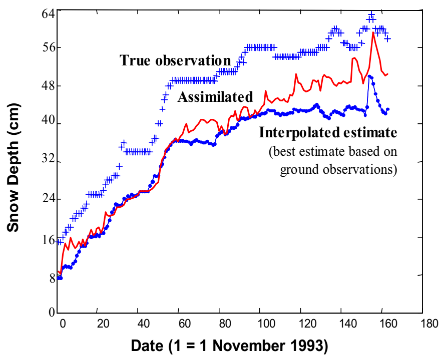

Figure 5. Improvement of SD estimation accuracy for a single test station (Erbogacen, Siberia) obtained by the assimilation of SSM/I data to interpolated SD value.

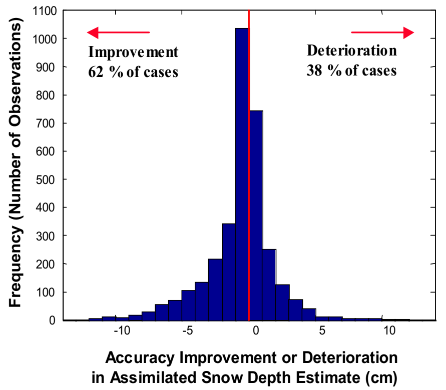

Figure 6. Histogram of the improvement/deterioration of Snow Depth (SD) estimation accuracy when SSM/I data are assimilated to interpolated SD estimates. The results are determined for 22 test stations around Siberia and northwestern Russia.

4.3 *Potential of data assimilation in the case of water quality forecasting*

Fig. 7 demonstrates the high potential of combining optical satellite spectrometer data with hydrodynamic ecosystem models. Fig. 7 shows the modeled water quality (phytoplankton biomass) and satellite data-derived water turbidity value for the Neva Estuary in the Gulf of Finland. The depicted results show that remote sensing data- based estimates on water quality characteristics yield spatial behavior patterns that are similar to those obtained by ecosystem models. This indicates that the assimilation of remote sensing data to ecosystem models can probably significantly improve the spatial accuracy of models, especially in hot spot regions where the spatial variability of water quality is high, as in the Gulf of Finland.

As hydrodymic ecosystem models are often complicated 3-D models, linear assimilation techniques, such as extended Kalman filtering, are more feasible for operative use than iterative non-linear methods.

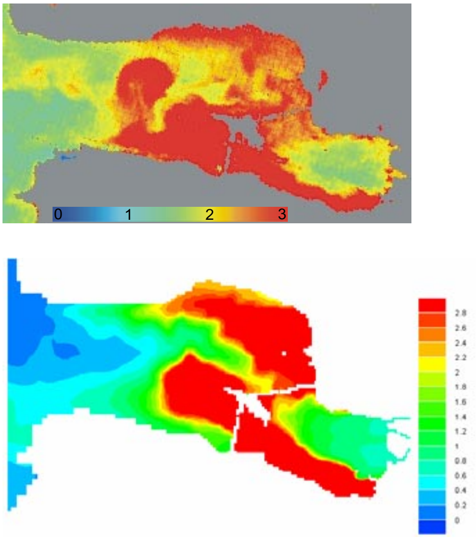

Figure 7. Turbidity (FNU) derived from MODIS spectrometer data (above) and phytoplankton biomass (mg WW l^{-1}) simulated with the Ecosystem Model of the Finnish Environment Institute (below) in the Neva Estuary on August 27, 2000.

5 CONCLUSION

The obtained results indicate that the satellite data assimilation is a potential tool for improving the performance of operative environmental models. Iterative methods can be used when remote sensing data is combined with relative simple models, such as conceptual discharge/runoff prediction models (quasi-2D-models). In this investigation we tested these methods successfully with the operational Finnish WSFS-model. As well the iterative assimilation methods demonstrated here appear to be feasible for combining satellite data with estimates on geophysical variables spatially interpolated from discrete ground observations.

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