Merging microwave radiometer data and meteorological data for improved sea ice concentrations

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ABSTRACT

The paper describes a method that can be used to evaluate the importance of various aspects of the parameter retrieval problem in microwave radiometry. The method is based on linear estimation theory, and allows the combination of microwave and meteorological/climatological data. Results are presented that show the importance of an improved knowledge of tie point emissivities (the signature of various ice types) and also the possibilities of improving the retrieved ice concentrations by adding meteorological and/or climatological information about sea surface and atmospheric parameters.

Keywords: Microwave radiometry, sea ice, parameter retrieval, SMMR, climatology.

1. INTRODUCTION

The purpose of the present paper is to describe a method by which retrievals of sea ice concentration from passive microwave observations can be evaluated.

Algorithms and results presented in the literature, i.e. Svendsen et al, (1983), Comiso (1983 & 1986), Swift et al. (1985), Cavalieri & Gloersen (1984), Gloersen & Cavalieri (1986), so far have all been based on quite severe approximations/simplifications to the radiative transfer process through the atmosphere. The number of variables describing this process has been reduced from infinity (atmospheric profiles) to very few if any at all. Basically, we are faced with a problem where we have a very limited number of equations (measurements) to solve for an unlimited or at least very large number of unknowns. The simplifications were carried out with reference to the fact that atmospheric influence is minimal in the Arctic regions and thus may be more or less neglected. However, the results presented have shown that the algorithms are quite sensitive to geophysical noise, ie. the fact that variations in other geophysical parameters are misinterpreted as variations in ice concentration. Cloud liquid water content, atmospheric water vapour, wind induced surface roughness and air/ice temperature (Pedersen, 1991) are important contributors. It is therefore of great interest to be able to include knowledge about these parameters in the retrieval process. As an example: if the wind speed is known from other sources (with some uncertainty) it may be used to improve the ice parameter retrieval because it reduces one of the uncertainties.

The method presented in the following shows how to incorporate the necessary à priori knowledge in order to reduce the number of variables to the number of equations (or less), and allows us to quantify the importance. The method is based on linear estimation theory which may be applied to this non-linear problem within a limited range of parameters or using iterative solutions. A major result of the method presented is the quantification of the effect of using à priori constraints on the solution such as climatological information about seasonal and regional variability of the geophysical parameters. Another major result is that the method provides the standard deviation of the best possible solution, and a way to obtain this solution. However, as will be shown, this solution is not easily reached in our case, but the purpose of all parameter retrievals should be to come as close as possible to this solution, and the best possible solution is a good basis to compare with.

Data from the NIMBUS-7 SMMR will be used to exemplify the results obtained.

2. THEORETICAL BACKGROUND

The basic radiative transfer equation states that the antenna temperature T_A measured by an antenna at a satellite platform may be expressed as a non-linear function F, of a number of geophysical parameters relevant to the measurement situation

$$T_A(f, \theta, p) = F(SST, WS, WV(z), CLW(z), T_{air}(z), T_{ice}, C,., e_t..) \quad (1)$$

where

SST	is sea surface temperature
WS	is wind speed
WV(z)	is atmospheric water vapour profile
CLW(z)	is cloud liquid water profile
$T_{air}(z)$	is atmospheric temperature profile
T_{ice}	is ice temperature
C	is total ice concentration
e_t	is tie point emissivity
f	is microwave frequency
θ	is incidence angle
p	is polarisation

Solving equation (1) for the geophysical parameters is an ill-posed or under-constrained problem because several of the unknown parameters are continuous functions of altitude, z, and there are only a finite number of measurements. The results presented in the following will be based on a limited subset of these parameters, but may in principle incorporate any number. In order to be able to simplify the following calculations and use vector and matrix algebra, the approach taken here is to approximate F with a linear function of a finite number of variables.

$$\mathbf{T_A} = \mathbf{F(p)} \quad (2)$$

where $\mathbf{T_A}$ is a vector with a finite number of antenna temperatures (channels at different frequencies, incidence angles and polarizations) and **p** is a vector with a finite number of geophysical parameters. In the following bold face letters are used to denote vectors and matrices and superscript t is used to denote matrix transpose.

In the present example, the number of variables is reduced to 7

$$\mathbf{p} = (SST, WS, WV, CLW, T, C, F) \quad (3)$$

where SST and WS are the same as above, WV is the integrated columnar atmospheric water vapour content, CLW is the integrated cloud liquid water content, T is the surface air temperature which is related to the ice temperature through

$$T_{ice} = 0.4\,T + 0.6\,SST \qquad (SST = 272K)$$

from Svendsen et al (1983). C is total ice concentration and F is multiyear ice fraction.

These 7 geophysical parameters are by experience the most important ones influencing the amount of microwave radiation received at satellite altitude at frequencies in the 5-40 GHz. range.

A couple of simplifications requires a comment: altitude variations of the atmospheric temperature, pressure and water vapour content are modelled as US standard atmosphere 1962 (Ulaby et al, 1981), whereas the cloud liquid water content is modelled as equally distributed between 400 and 500 meters. The other major simplification is the fact that only two ice types are considered, First-year (FY) and Multiyear (MY) and that snow cover over the ice is considered to be always present. This imposes a serious limitation in certain parts of the year (new ice formation and summer melting), but in order to show the basic principles of the method and to obtain further insight into the parameter retrieval problem, the simplifications are of minor importance.

The $\mathbf{T_A}$ vector simply consists of the antenna temperatures at a finite number of frequencies, most often at one fixed incidence angle and at one or both horizontal and vertical polarizations. The examples that will be presented are based on data from the NIMBUS-7 SMMR, and in that case $\mathbf{T_A}$ consists of 10 dual-polarized temperatures at the 5 frequencies 6.6, 10.7, 18, 21 and 37 GHz and an incidence angle of 50 degrees.

The functional relationship **F** between geophysical parameters and microwave emission is reasonably well known (Wilheit, 1979, Wentz, 1983, Ulaby et al, 1981+1986) and a block diagram of the implemented combined atmosphere-ice-ocean emissivity model is presented in **Figure 1**.

However, such models all produce antenna temperatures as a function of geophysical parameters whereas the problem we are facing when presented with data from a certain satellite microwave radiometer is that of inverting the nonlinear function to produce geophysical parameters from the measured quantities.

2.1 Linear estimation

The discrete version of our model equation (2) in matrix terms reads

$$\mathbf{T_A} = \mathbf{Mp} \quad (4)$$

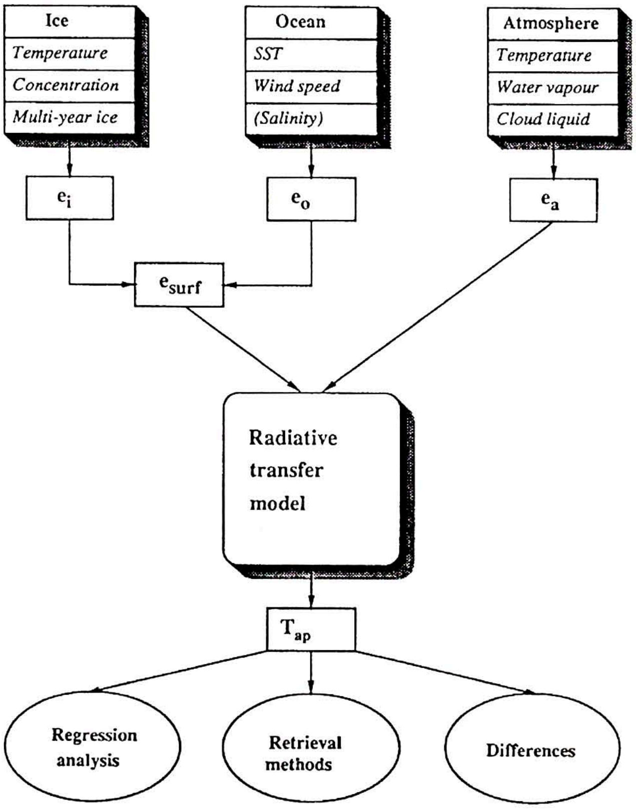

Fig. 1 - Diagram showing the outline of the model complex utilised in this study

where the matrix **M** consists of the partial derivatives of the function **F**

$$\mathbf{M}_{ij} = \frac{\delta\, \mathbf{T}_{Ai}}{\delta\, \mathbf{p}_j} \tag{5}$$

In the case where the number of independent measurements is larger than the number of unknown geophysical parameters, we may obtain a least squares solution to (4)

$$\hat{\mathbf{p}} = (\mathbf{M}^t\mathbf{M})^{-1}\, \mathbf{M}^t\, \mathbf{T}_A \tag{6}$$

which can be obtained if $\mathbf{M}^t\mathbf{M}$ can be securely inverted, i.e. if the number of measurements are independent. In the case of the NIMBUS-7 SMMR with 10 measurements and 7 geophysical parameters this is generally possible.

However, the measurements of T_{Ai} are not absolute but are connected with a certain measurement error (error bars) due to the stochastic nature of the thermal radiation and due to instrument noise. This means that equation (4) should read

$$\mathbf{T}_A = \mathbf{Mp} + \mathbf{e} \tag{7}$$

where **e** is considered normally distributed with a covariance matrix $\mathbf{S}_e$. Linear estimation theory now gives the least squares estimate of **p**

$$\hat{\mathbf{p}} = (\mathbf{M}^t\, \mathbf{S}_e^{-1}\, \mathbf{M})^{-1}\, \mathbf{M}_t\, \mathbf{S}_e^{-1}\, \mathbf{T}_A \tag{8}$$

and the covariance of this estimate

$$\hat{\mathbf{S}} = (\mathbf{M}^t\, \mathbf{S}_e^{-1}\, \mathbf{M})^{-1} \tag{9}$$

from which we get the simplest possible measure of the uncertainty of the solution since the diagonal elements contains the variances or squared standard deviations of each of the estimated geophysical parameters. Notice that this is the optimum solution, i.e. the smallest obtainable standard deviations, the best precision.

The effect of the measurement is to map geophysical parameter space into T_A-space, and the retrieval problem is to map measurement space (T_A-space) back into geophysical parameter space (Rodgers, 1976). The covariance matrix **S** now determines how the error bars of the measurements (T_A) expressed by the error covariance $\mathbf{S}_e$ map onto the error bars of the solution (Rodgers, 1976).

2.2 Geophysical constraints

Up till this point we have put no restrictions on the variations of the estimated geophysical parameters. However the estimate may be further improved by the use of à priori information (f.ex. from climatology) about the mean and covariances of the geophysical parameters.

The way to do this is to consider the à priori information as another set of measurements of the unknown parameters with mean value $\mathbf{p}_0$ and covariance $\mathbf{S}_p$.

The way to combine such two sets of estimates of an unknown quantity is to take a weighted average of them, with the reciprocal of their covariances as weights. The resulting covariance is

$$\hat{\mathbf{S}} = (\mathbf{S}_p^{-1} + \mathbf{S}_D^{-1})^{-1} \tag{10}$$

where $\mathbf{S}_D$ is the covariance of the parameters estimated solely from the radiometer measurements, i.e. (9). Inserting (9) for $\mathbf{S}_D$ in (10) leads to

$$\hat{\mathbf{S}} = (\mathbf{S}_p^{-1} + \mathbf{M}^t\, \mathbf{S}_e^{-1}\, \mathbf{M})^{-1} \tag{11}$$

The estimate of **p** is

$$\hat{\mathbf{p}} = (\mathbf{S}_p^{-1} + \mathbf{S}_D^{-1})^{-1}\, (\mathbf{S}_p^{-1}\, \mathbf{p}_0 + \mathbf{S}_D^{-1}\, \mathbf{p}_1) \tag{12}$$

where $\mathbf{p_1}$ is the estimate based solely on the radiometer measurements (8). Inserting (8) in (12) and rearranging we obtain the following expression for the estimate

$$\hat{\mathbf{p}} = \hat{\mathbf{S}} (\mathbf{S}_p^{-1} \mathbf{p}_0 + \mathbf{M}^t \mathbf{S}_e^{-1} \mathbf{T}_A) \quad (13)$$

where **S** is given by (11). Note that because of the nonlinearities, the solution (13) must be obtained by iteration and the matrix **M** must be evaluated at each step. This is equivalent to saying that the relative importance of the various geophysical parameters are different at different ice concentrations, i.e. wind is important at low but not at high ice concentrations etc. This is also the reason why the following investigations of (11) are carried out at 4 points in the parameter space. Also, the use of equation (13) requires a model which is absolutely calibrated with respect to the given instrument, whereas only relative calibration is sufficient for the evaluation of (11). The implementation of (13) could be the subject of a later investigation.

2.3 Emissivity variations

In a previous study (Pedersen, 1991) it was concluded that the most important factor limiting the performance of ice concentration and ice type algorithms is regional and seasonal variations in tie point emissivities.

The way to quantify this effect is to consider the tie point emissivities, e_t, as unknown parameters to be estimated by the retrieval process along with C,F,SST,WS,etc.

The à priori knowledge consists in this case of mean values, which are the tie points, and standard deviations, which represent the uncertainty.

The partial derivatives are computed from intervals of 0.02 around the tie point values

$$\frac{\delta T_A}{\delta e^t} = \frac{T_{A1} - T_{A2}}{0.02} \quad (14)$$

and the covariance matrix is constructed from the following rules:

- Diagonal elements are the specified variance of the tie point emissivities (typically 0.05^2 to 0.01^2), the same for all channels.
- Off diagonal elements are 0 (zero), considering the emissivity variations to be uncorrelated. This corresponds to a worst-case situation (Rodgers, 1976).

Thus, the inclusion of the emissivities as unknowns increases the number of unknowns to 27, and disables any solution that does not incorporate some kind of à priori constraints (the types described in equation (6) and (8)) because we now have more unknowns than measurements from a 10 channel radiometer.

3. DATA SETS / MODELS

In order to use the theory described in the previous sections, a number of data sets are necessary. Looking at (11) the quantities on the right hand side of the equation are:

M the matrix of partial derivatives
$\mathbf{S_p}$ the covariance matrix of the geophysical parameters
$\mathbf{S_e}$ the measurement error covariance matrix

and they are all needed in order to find the covariance of the estimated geophysical parameters from the optimal retrieval method. The following sections will present a number of examples of results from this equation using various right hand sides, and here the individual elements are presented.

3.1 Matrix of partial derivatives

The matrix **M** is computed using a set of models of the microwave emission from an ocean/ice surface and for the transmission through the atmosphere. The model function is described in equation (1) with the addition of 20 emissivities to the vector of parameters. Thus, at a certain microwave frequency, polarization and incidence angle, the apparent temperature may be computed as a function of sea surface temperature, wind speed, integrated columnar water vapour and cloud liquid water, air/ice temperature, ice concentration, multiyear ice fraction and tie point emissivities (FY and MY-ice)

The partial derivative of T_A with respect to a certain of these parameters p_i is now estimated by keeping all parameters constant except p_i and computing T_A at two (close) values of the desired parameter.

Table 1 lists minimum, maximum and default values for each of the geophysical parameters.

Table 1 - Parameter intervals used for the computation of partial derivatives. The default values are the values taken by the parameters when one of the others is being varied.

		Minimum	Maximum	Default
SST	°C	-1.75	2.25	-1.75
WS	m/s	5.0	10.0	8.0
Water vapour	cm.	0.2	0.8	0.4
Air temperature	°C	-20.0	-10.0	-15.0
Cloud liquid water	10^{-3} cm	0.0	20.0	0.0

The matrix of partial derivatives is evaluated at two points in FY-MY-Water space because of the nonlinear nature of the problem, i.e. the partial derivatives varies with for instance ice mixture and concentration. The two points are given in Table 2, and they allows us to evaluate parameter retrievals in each of these two situations, low ice concentration and high ice concentration.

Table 2 - The two combinations of total ice concentration (C) and multi year ice fraction (F) at which the matrix of partial derivatives has been evaluated for the present study.

	Total ice concentration	Multiyear ice fraction
Open ocean	10%	50%
First year ice	90%	10%

3.2 Covariance matrix of the measurements

This matrix is the full 10-dimensional covariance matrix of the error bars of the measurements. By nature the microwave emission is a noise signal with a certain mean value, and the way to get a good estimate of this mean value is by integrating over a long time. System design in scanning satellite systems sets an upper limit to the time available and also instrument noise adds to the uncertainty of the measurement. Information about instrument behaviour in this sense is typically available as the system sensitivity at each of the 10 channels. The off-diagonal elements of the S_e matrix are zero, since the measurement errors for the different channels are independent. The noise covariance matrix used in this study has all diagonal elements set to $(0{,}5K)^2$, corresponding to what is obtained from the spatial averaging of the NIMBUS-7 SMMR CELL data.

3.3 Covariance matrix of the geophysical parameters

The $\mathbf{S_p}$matrix represents the à priori knowledge of the geophysical parameters influencing the retrieval. They may vary regionally and seasonally but in the examples presented here the matrix $\mathbf{S_p}$ is estimated from a combination of near simultaneous meteorological surface and radiosonde observations and SMMR-derived ice parameters during a one year period. However, different combinations are used in order to be able to evaluate various levels of à priori knowledge.

Sea surface temperature, wind speed and air temperature are conventional measurements, integrated columnar water vapour is derived from radiosonde measurements. Cloud liquid water content is the most difficult parameter to estimate in this context where we want to know it also in periods with ice cover where it cannot be derived from SMMR data. The method used to obtain a reasonable CLW dataset corresponding to the other observations has been to use SMMR derived information (by an algorithm published by Wilheit & Chang (1980)) and setting CLW to zero when ice is present. This was considered the best that could be done with the available information. Clouds above an ice cover generally consists of lower water content (ice particles) than over the ocean. However, near the ice edge the description is probably not adequate. Total ice concentration and multiyear ice fraction are derived from SMMR data using an adjusted version of the algorithm presented by Cavalieri and Gloersen (1986). Also, note that the matrices presented actually are only the upper left 7x7 elements of the 27x27 covariance matrices of the unknown parameters. The other 20 parameters are the tie point emissivities which are considered uncorrelated both among themselves and to the 7 geophysical parameters. This represents a worst case situation, since any known off-diagonal element will improve the retrieval (Rodgers, (1976))

Two datasets were used in the analysis, one from Jan Mayen, and one from Bear Island. The correlation matrices are quite similar even quantitatively, so a combined one representing typical sub-Arctic conditions (Greenland Sea) was produced by a combination of the two. The resulting correlation matrix is shown in Table 3, and the covariance matrix in Table 4.

Table 3 - Correlation matrix found by combining the matrices from Jan Mayen and Bear Island.

	SST	WS	WV	T	CLW	C	F
SST	1						
WS	-0.2	1					
WV	0.7	-0.2	1				
T	0.7	-0.2	0.8	1			
CLW	0.25	-0.1	0.25	0.3	1		
C	-0.5	0.1	-0.35	-0.45	-0.55	1	
F	-0.15	0	-0.1	-0.1	-0.2	0.3	1

Table 4 - Covariance matrix found by combining the matrices from Jan Mayen and Bear Island.

	SST	WS	WV	T	CLW	C	F
SST	5.3						
WS	-2.3	25.0					
WV	0.8	-6.0	0.25				
T	9.7	-6.0	2.4	36.0			
CLW	4.6	-4.0	1.0	14.4	64.0		
C	-23.0	10.0	-3.5	-54.0	-88.0	225.0	
F	-1.7	0	-0.3	-3.0	-8.0	30.0	25.0

Since the data originates from areas that are only seasonally ice covered and hardly has any multiyear ice at all, the covariance matrix is only representative for such areas. Also notice, that it represents the whole year, but in principle seasonal dependencies could be included as well.

High correlations (0.7-0.8) are seen between SST, WV and T_{air} which is what would be expected from the seasonal cycle of these parameters. Cloud liquid water was expected to be in the same group with a positive correlation to the others, but is seen to be substantially lower (0.25-0.3). This may be attributed to the nature of the CLW dataset and also to the fact that both sites (Bear Island and Jan Mayen) are situated near the marginal ice zone close to the track of clouds originating in much warmer areas. All temperature and atmospheric parameters are negatively correlated to total ice concentration which was also expected since ice concentration has the opposite seasonal cycle. Wind speed and MY-fraction are not correlated to any of the other parameters i.e. they vary independently. The result for MY-fraction may be less accurate because of the fact that the amount of multiyear ice is very low and F therefore quite noisy. The data presented here, thus, are not representative for higher Arctic conditions with respect to MY-ice.

In order to construct a dataset representative for more variable ice conditions, the variances presented in Table 5 were produced by increasing the standard deviation of C and F to 50% and the variances of the other parameters corresponding to different levels of à priori knowledge. Any non-zero element represents some à priori knowledge that will improve the retrieval (Rodgers, 1976).

Table 5 - Diagonal elements of covariance matrices corresponding to the 5 different levels of á priori geophysical knowledge used in this study. Numbers correspond to standard deviations, i.e. the square root of the diagonal elements.

	SST	WS	WV	T	CLW	C	F
	K	m/s	cm	K	cm	%	%
5	5.2	10.0	1.1	20	0.020	50	50
4	3.9	7.5	0.8	15	0.015	50	50
3	2.6	5.0	0.54	10	0.010	50	50
2	2.0	3.0	0.3	5	0.008	50	50
1	1.5	2.0	0.2	4	0.005	50	50

4. DISCUSSION

This section presents a number of examples illustrating the usefulness and possibilities of the estimation theory described.

Examples will be given of how the use of à priori knowledge about the variance and covariance of the geophysical parameters can improve the retrievals.

A subsection will quantify the effects of emissivity variations on the retrieval of ice concentration.

Throughout, two different channel combinations will be used:

1) 37 GHz horizontal and vertical polarization (37 H+V)
2) 37 and 18 GHz vertical polarization (18 + 37 V)

A standard deviation of ice emissivities of 0.01 is used in the investigation of à priori knowledge.

A standard deviation of 0.5K is used for measurement noise corresponding to the CELL data.

Climatological level of à priori information is assumed when investigating emissivity variations.

4.1 Emissivity variations

The seasonal and regional variability of the tie point emissivities is an important factor limiting the ability of determining ice concentration and ice type from passive microwave measurements. The purpose of this section is to quantify the importance of such variations and estimate the precision with which the emissivities must be known in order to obtain a certain retrieval accuracy for the ice parameters.

Tie point emissivities are treated in this exercise as unknown quantities to be estimated. They have a certain mean value (the expected tie point) and are associated with an uncertainty of et. Under winter conditions the variation in e_t is typically of the order of 0.01 or smaller whereas values in the melt periods may vary rapidly (by more than 0.05 in a few days or even hours). Also, the regional variations of especially the multiyear signature are significant and may easily be in the order of 0.05.

The correlation between different channels is unknown. The emissivity variations are mainly caused by variations in ice surface conditions and therefore must be correlated from channel to channel. A worst case example is obtained by considering the correlations to be zero.

Figure 2 shows the results for estimates of total ice concentration. As expected the influence is strongest at high ice concentrations, whereas it is of minor importance at low concentrations. At high ice concentrations the standard deviation of the retrieved ice concentration (i.e. the precision) drops drastically as the knowledge of tie point emissivities increases. It is seen that even if we know the emissivity of the ice within 0.02 this is still the major contribution to the uncertainty of the estimate. The situation may be somewhat improved by including more channels in the retrieval process.

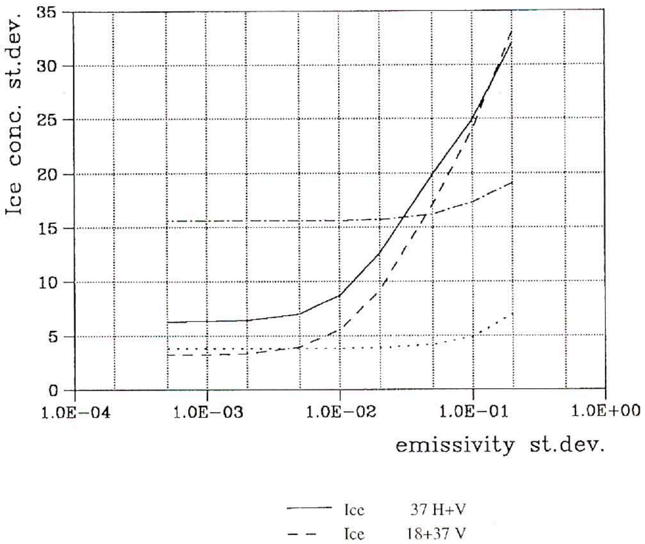

Fig. 2 - Standard deviation of retrieved ice concentration as a function of tie-point emissivity variability (i.e. knowledge). Full and dotted lines corresponds to low ice concentrations, dashed and dash-dotted to high ice concentrations as specified in Table 2

We may conclude that it is desirable to know the emissivity with an accuracy of at least 0.01 which is far better that what we know today, in particular during periods of rapid surface variations.

4.2 À priori constraints

In this section it will be considered how the retrieval of the ice parameters can be improved by the use of à priori knowledge of the variance and covariance of the geophysical parameters.

The basic assumption here is that the solution (8) allows for large variations in the ocean and atmospheric parameters and actually they will often take unrealistic values due to the fact that we do not have sufficient independent measurements and that the measurements are noisy. Such unrealistic values may be negative wind speeds or unrealistically high wind speeds, sea surface temperatures below the freezing point of sea water etc.

The way to limit these variations is to apply à priori knowledge such as climatology, and equation (10)-(13) give the theoretical details of how to do it. We use the climatological covariance matrix which may be derived on a regional and seasonal basis in order to take the full advantage of more detailed knowledge. The following show how we can improve the estimates this way, and how much knowledge is necessary in order to do so.

Five different covariance matrices for the geophysical parameters have been used as described earlier corresponding to the following five situations (see table 5)

1) Variances corresponding to meteorological analysis fields (best à priori knowledge).
2) Same as 1), but with somewhat larger variances, corresponding to a more pessimistic estimate of the performance of the meteorological analysis model.
3) Variances corresponding to climatological observations.
4) As 3) only with somewhat larger variances corresponding to worse climatology or more variable conditions.
5) Worst case climatological data (guessed)!

Figure 3 shows the results of the estimations based on different levels of à priori knowledge. It is seen that the major effect is at low ice concentrations whereas it is of minor importance at high concentrations. In particular it is very important if we use the polarization algorithm at 37 GHz. In this case it would be possible to improve

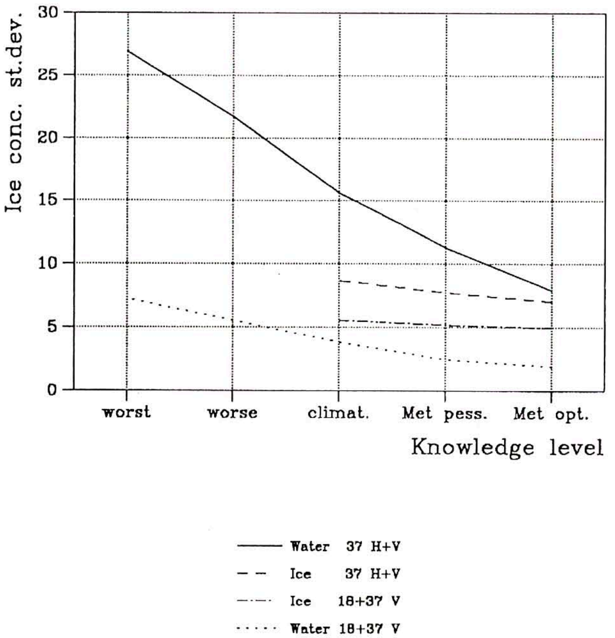

Fig. 3 - Standard deviation of estimated ice concentrations as a function of the level of à priori knowledge. Full and dotted lines corresponds to low ice concentrations, dashed and dash-dotted to high ice concentrations as specified in Table 2.

the estimation precision from approx. 15% to about 8% if better knowledge about the atmospheric and sea-surface parameters is available. But even with the 18+37 GHz algorithm a substantial improvement (4% to 2%) is at hand if we have access to reliable meteorological analysis fields or short term forecasts to help the retrievals.

CONCLUSIONS

It has been shown how the application of linear estimation theory may improve our understanding of the nature of the sources of errors in parameter retrieval from passive microwave measurements.

Examples from NIMBUS-7 SMMR have been used throughout, and some of the major results are:

Emissivity variations: Very important at high ice concentrations.

À priori Knowledge: At low ice concentrations this is very important. A major improvement may be obtained by introducing meteorological analysis fields instead of the previously used climatology.

The theory described does allow for evaluation of all the important parameters as long as their effect can be modelled. This includes the possibility of adding more unknowns such as cloud height and temperature, atmospheric lapse rates etc. This is an obvious task for future research.

The theory may also provide results about the estimation of ocean and atmospheric parameters with or without the presence of sea ice.

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