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CORRECTING SOLID PRECIPITATION DATA FROM GAUGE OBSERVATIONS USING PASSIVE MICROWAVE BRIGHTNESS TEMPERATURE DATA

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In this paper a basic study is presented to develop a method to correct solid precipitation data from gauge observations using the passive microwave brightness temperature data and data assimilation.

Observation and modeling results are indicating a high sensitivity of the 89 GHz channel to fresh snow on the ground. The change in the brightness temperature due to snow is used to correct observed solid precipitation data. The old brightness temperature data, the adjusted precipitation and the density of the fresh snow are input parameter for a radiative transfer model. The result is compared with the new brightness temperature and by iteration the precipitation data is adjusted until the modeled value agrees well with the new brightness temperature.

Good results have been achieved using snow pit data from Sapporo and modeled brightness temperatures. A sensitivity analysis showed, that this cost minimization problem has a unique solution.

Key Words: *Passive Microwave Brightness Temperature, Solid Precipitation Observation, Snowfall, Radiative Transfer Model, Snow Mode, Simulated Annealing*

1. INTRODUCTION

Due to its heigh albedo and thermal insultaion, snow plays an important role in the global energy and water balance and the monitoring of long term changes in the snow storage is providing valuable information for global climate change studies. But also for local water resources problems, snow is an important factor. For example it changes the runoff characteristics of a catchment and influences soil moisture and evaporation[1].

The Climate and Cryosphere (CliC) Project stated, that "Knowledge of the amount, distribution, and type of precipitation and its temporal and spatial variability on a wide range of scales, is essential for the study of cold climate and related hydrological processes"[2].

Reliable snowfall observation data using precipitation gauges is difficult to obtain. This is due to systematic problems of the observation method. Due to wind-induced undercatch or evaporation only some part of the actual precipitation is observed by the gauge[3].

Observed and modeled brightness temperature data at 89 GHz is showing a high sensitivity to fresh snow on the ground. In this study this fact is used to start the development of an algorithm to correct observed precipitation data by evaluating the catch efficiency of the gauge. This is done by relating the change in the brightness temperature to the total amount of new snow on the ground.

Several satellite algorithms are available to estimate the snow depth and snow water equivalent of a snow covered area. These algorithms are using frequencies at 19 and 36 GHz[4]. Fresh snow

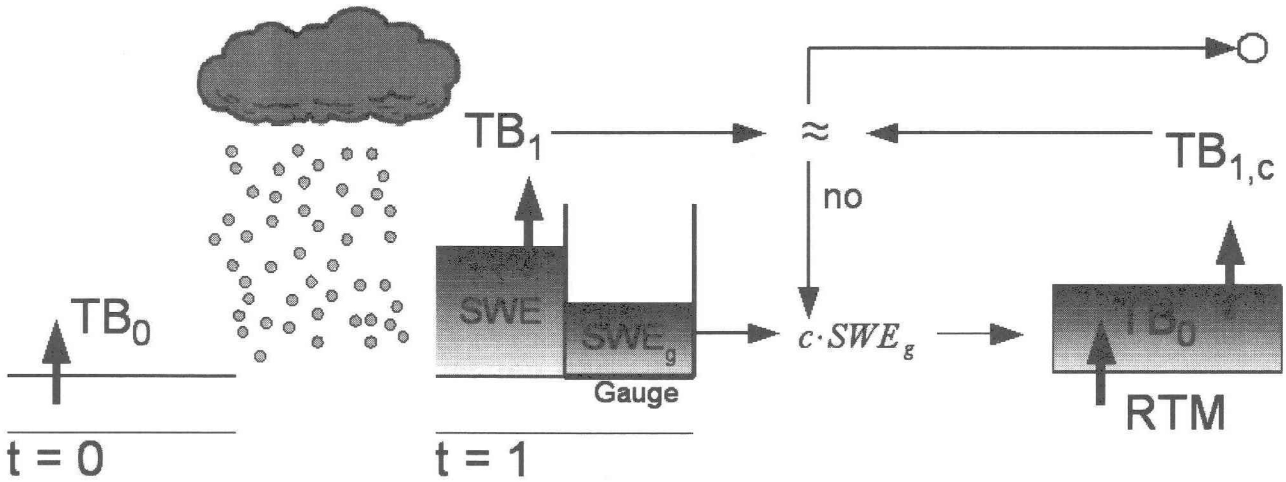

Fig. 1 Algorithm Overview

on the ground is transparent at these frequencies and therefore these algorithms can't be used to related the change of SWE or snow depth to the actual solid precipitation.

2. METHODOLOGY

(1) Algorithm Description

The brightness temperature observation of a snow covered land surface depends on the physical properties of the snow, including the size of the snow grains and the density of the snow pack, and the emission of the underlying ground. If these physical properties are known, it is possible to estimate the brightness temperature at the surface of the snow layer using a radiative transfer model. But due to the complex vertical heterogeneity of a snow pack (e.g. grain size), it is difficult to directly retrieve snow pack properties using brightness temperature observation. Therefore in this study a data assimilation scheme is used to couple a radiative transfer model and a snow (accumulation) model to compare brightness temperature data and the properties of fresh snow on the ground.

The brightness temperature at 89 GHz is showing a high sensitivity to the amount of fresh snow on the ground. Therefore it is possible to relate the change in the brightness temperatures at this frequency between two different times (at $t=0$ and $t=1$) to the accumulated new snow. The advantage of this algorithm is, that it is not necessary to know the physical properties of the old snow. In addition the fresh snow on the ground can be assumed to have a homogenous vertical profile, which further simplifies the problem.

Fig. 1 provides an overview of the algorithm. The gauge data (SWE_g), the first guess of the correction factor (c) and the density of the new snow are input parameters for a snow model. The result of the snow model and the brightness temperature for the old snow (TB_0) are then used to calculate the radiative transfer in the fresh snow. The results of the radiative transfer model ($TB_{1,c}$) are then compared with TB_1. During the assimilation process, the correction factor for the observed solid precipitation and the new snow density will be updated, until $TB_{1,c}$ is in good agreement with TB_1.

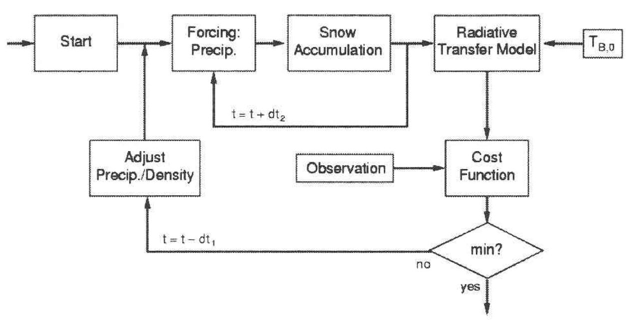

Fig. 2 Data Assimilation

An important assumption in this algorithm is, that TB_0 does not change between the two observations. Snow grain size, density and temperature are parameters, which can influence the brightness temperature. The change of the grain size and the density are small within the selected time period between $t=0$ and $t=1$, e.g. 1 day, and therefore the effect of the change on TB_0 can be neglected. The temperature of the snow cover can change by several degrees during a day, but the effect on the TB is small due to the low emissivity of dry snow.

Fig. 2 provides an additional overview of the data assimilation process. The cost function is minimized by adjusting the correction factor for the observed precipitation and the density of the new snow. These parameters are updated using an heuristic minimization method called simulated annealing[5]. This method was successfully applied to the assimilation of soil moisture data[6].

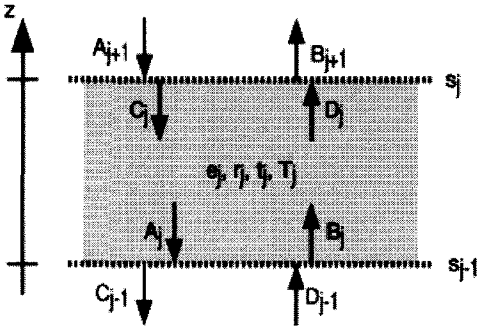

Fig. 3 MEMLS vertical Fluxes

(2) Cost Function

The assimilation scheme is used to minimize the cost function J by adjusting a state vector x[7]. In general J can be separated into two different costs, one represents the background error J_B and the other one the observation error J_0:

$$J = J_B + J_0 \qquad (1)$$

The background error J_B expresses the change of the initial conditions from the first selected initial state. For this application the initial state (x_0) of the snowpack is not changed, because only new accumulated snow is considered and therefore J_B can be neglected. J then reduces to the observation error J_0, which usually expressed the difference between the observed and modeled values by considering the error covariance matrix R:

$$J = J_0 = \frac{1}{2}\sum_{i=1}^{N}\left(H[x_i] - y_i^0\right)^T R^{-1}\left(H[x_i] - y_i^0\right) \qquad (2)$$

y_i^0 is a vector representing the satellite observation at 89 GHz (vertical and horizontal polarization), which will be assimilated. H is the radiative transfer model (observation operator) and R is the error covariance matrix of the observation. x_i represents the state vector at t_i calculated by the snow accumulation model M (model operator) using the state vector x_0 at t_0 as initial conditions and forcing data f. The forcing data includes also the corrected precipitation data. The state vector x_i comprises the snow height and density:

$$x_i = M(x_0, f) \qquad (3)$$

x_0 represents the initial state of the snowpack. In this scheme only the accumulation of new snow is considered, therefore x_0 represents a state with no snow on the ground. Combining Eq. (2) and Eq. (3) yields the cost function for the assimilation scheme:

$$J(x_0, f) = \frac{1}{2}\sum_{i=1}^{N}\left(H[M(x_0, f)] - y_i^0\right)^T \cdot R^{-1}\left(H[M(x_0, f)] - y_i^0\right) \qquad (4)$$

The equation above shows that the brightness temperature data is directly included into the minimization process of the cost function J. Which means, that the state of the modeled and real snow pack can be compared by comparing modeled and observed brightness temperatures.

(3) Model Operatore

In this application a simple snow model is used as model operator, which calculates the accumulated snow height on the basis of the corrected precipitation data and estimated snow density.

The settlement of the snow is estimated by calculating the viscous compression[8]:

$$\frac{d\rho_s}{dt} = \frac{W}{\eta}\rho_s \qquad (5)$$

where ρ_s represents the density of (dry) snow, W the overburden snow load and η the compactive viscosity coefficient, which can be calculated as[8]:

$$\eta = \eta_0 \cdot \exp(K\rho_s - \alpha_s T) \qquad (6)$$

where $\eta_0 = 6.9 \cdot 10^5$ kg·s/m, $K = 2.1 \cdot 10^{-2}$ m^3/kg and $\alpha_s = 9.58 \cdot 10^{-2}$ /°C.

This simple approach was selected, because for this application only the accumulation of the new snow is of interest. More detailed processes like snow grain growth can be ignored because of the short time period of interest.

(4) Observation Operator

The Microwave Emission Model of Layered Snowpack[9] (MEMLS) with the extension for coarse-grained snow[10] was selected as radiative transfer model. This model was explicitly developed for the snow case and successfully applied in Switzerland[11], where the situation of the snow pack is similar to Sapporo.

The vertical fluxes in a multi-layered media can be express by four up- and down-welling brightness temperatures (see also Fig. 3):

$$A_j = r_j B_j + t_j C_j + e_j T \qquad (7)$$

$$B_j = s_{j-1} A_j + (1 - s_{j-1}) D_{j-1} \qquad (8)$$

$$C_j = (1 - s_j) A_{j+1} + s_j D_j \qquad (9)$$

$$D_j = t_j B_j + r_j C_j + e_j T_j \qquad (10)$$

where e_j represents the layer emissivity, r_j represents the layer reflectivity, t_j the layer transmissivity, T_j the layer temperature and s_j the interface reflectivity between layer j and j+1. For a snowpack with n layers A_{n+1} represents the sky brightness and D_0 the emission from the ground.

By introducing Eq. (8) and Eq. (9) into Eq. (7) and Eq. (10) this system can be solved if A_{n+1} and D_0 (boundary conditions) and e_j, r_j, s_j and t_j are known. A_{n+1} and D_0 are the sky brightness and the soil temperature. The parameters e_j, r_j, and t_j can be calculated from snow-pack properties by introducing a six-flux radiative transfer model and the improved born approximation.

In the six-flux model the radiation for a given polarization and frequency is reduced into two vertical (T_1 and T_2) and four horizontal streams (T_3 and T_6). The horizontal fluxes are representing trapped radiation, which can't leave a layer, but are couple with the horizontal fluxes due to scattering. Since snow is a plane parallel and istropic medium in the x,y plane, it is possible to reduce the six-flux model to a 2 flux model with adjusted coefficients for absorbtion (γ_a') and scattering (γ_b'):

$$-\frac{dT_1}{dz}|\cos\theta| = -\gamma_a'(T_1 - T_s) - y_b'(T_1 - T_2)$$
$$-\frac{dT_2}{dz}|\cos\theta| = -\gamma_a'(T_2 - T_s) - y_b'(T_2 - T_1) \tag{11}$$

θ represents the observation angle for the brightness temperature measurements. For constant coefficients in a layer eq. (11) can be rewritten as:

$$T_1 = T + A\cdot\exp(\gamma\cdot d') + B\cdot\exp(-\gamma\cdot d')$$
$$T_1 = T + r_0\cdot A\cdot\exp(\gamma\cdot d') + r_0\cdot B\cdot\exp(-\gamma\cdot d') \tag{12}$$

where:

$$\gamma = \sqrt{\gamma_a'(\gamma_a' + 2\gamma_b')} \tag{13}$$

$$d' = d/|\cos\theta| \tag{14}$$

r_j, and t_j can be calculated from:

$$r = r_0(1 - t_0^2)\cdot(1 - r_0^2 t_0^2)^{-1} \tag{15}$$

$$t = t_0(1 - r_0^2)\cdot(1 - r_0^2 t_0^2)^{-1} \tag{16}$$

r_0 and t_0 are given by:

$$r_0 = \gamma_b'(\gamma_a' + \gamma_b' + \gamma')^{-1} \tag{17}$$

$$t_0 = \exp(-\gamma\cdot d') \tag{18}$$

The emissivity e_j is calculated as:

$$e = 1 - r - t \tag{19}$$

The layer reflectivity s_j is calculated on the basis of the Fresnel reflection coefficient (F_j):

$$s_j = |F_j|^2 \tag{20}$$

The observed brightness temperature can then be calculated by:

$$TB_{calc} = s_n A_{n+1} + (1 - s_n)D_n \tag{21}$$

(5) Simulated Annealing

To reduce the cost function of the assimilation scheme, a heuristic method called simulated annealing is introduced. This method can find the global minima in the surface spanned by the cost function.

Compared to adjoint models simulated annealing has advantages in dealing with non-linearities and discontinuities. It is able to solve the problem of data assimilation into an almost steady state for a simple, highly non-linear model[12]. The approach used by simulated annealing is an analogy to thermodynamics (annealing of metal)[13].

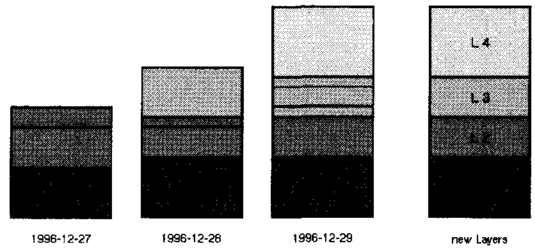

Fig. 4 Snowpack Layer

The change of the assimilation parameters is constrained by the lower and upper limit of all possible values:

$$x \in [R_l, R_u] \tag{22}$$

where x is the vector of assimilation parameters with dimension n and R_l respectively R_u are representing the lower and upper limits of x. The state vector x is updated by an random increment δx:

$$x_{i+1} = x_i + \delta x(R_u - R_l) \tag{23}$$

The generation of the random increment δx and the annealing schedule governs the performance of the assimilation. The generating function is defined by[13]:

$$\delta x^j = \operatorname{sgn}\left(u^j - \frac{1}{2}\right)T^j\left[\left(1 + \frac{1}{T^j}\right)^{|2u^j - 1|} - 1\right] \tag{24}$$

where u^j is a uniform distributed random number ($u^j \in [0,1]$) and j represents the j-th element of the state vector.

The annealing schedule for T^j is:

$$T_i^j = T_0^j\cdot\exp(-c\cdot i^{1/n}) \tag{25}$$

where n is the dimension of the state vector and c an analogy of the Boltzmann constant.

3. Data

For the application of the algorithm snow pack observations for the winter season 1996/97 in Sapporo, Japan have been used. This data contains an intensive data set of daily snow pits as well as detailed forcing data including precipitation and wind speed. The brightness temperature data was calculated using the snow-pit data and MEMLS.

(1) Snow-pit Data

In a first step continuous periods have been identified, during which snowfall occurred. Most of the periods comprises of three or four observation. Several changes to the snow pack data have been necessary to avoid problems due to errors in the observation of the snow pack density. The data was corrected by identifying corresponding layers in each snow pack data set and calculating an average layer density. Fig. 4 shows an example how the layers were re-arranged. It is assumed, that the snow water equivalent of the new layers 3 and 4 are also representing the correct amount of new snow (precipitation) between the 27^{th} and 28^{th} (layer 3) and between 28^{th} and 29^{th} (layer 4).

(2) Forcing Data

The corresponding data set contains solid precipitation, air and snow surface temperature, wind speed and direction, relative humidity, up- and downward short- and long wave radiation and ground heat flux. For this study only the observed precipitation data was used.

Snowfall observations using a precipitation gauge are often strongly underestimating the actual snowfall. In this study it is assumed, that the observed increase in the SWE is equal to the actual snowfall (see section 3.1) and that the gauge observation are corrected during the assimilation.

Fig. 5 provides a comparison between the increase of the snow water equivalent between two days and the observed precipitation. There are two main factors, which can explain the difference between the observations. First, as mentioned, in most cases the catch efficiency of a gauge is less then one, therefore the observed solid precipitation is lower then the actual snowfall. The second reason is the redistribution of snow due to wind blowing. This effect can cause an increase (accumulation) or a decrease (ablation) of snow at the snow pit location. A problem with the snow pit data was in some cases the very high density of the new snow. Values higher then 150 kg/m^3 are probably caused by an observation error in the field.

(3) Brightness Temperature Data

The brightness temperature data was created using the corrected snow pit data set. In a first step the *TB* of the snow pack at *t=0* was calculated by using the radiative transfer model. This result was used as input for the estimation of the *TB* at *t=1*, where the radiative transfer was calculated using the properties of the fresh snow. For example for the case from Dec. 28^{th} to Dec. 29^{th} (see Fig. 4) first the radiative transfer through layer 1 to 3 is calculated (TB_0). The results are then used for calculating the radiative transfer through layer 4, which represents the brightness temperature data (TB_1). As mentioned changes of TB_0 because of changes in the layer 1 to 3 are neglected.

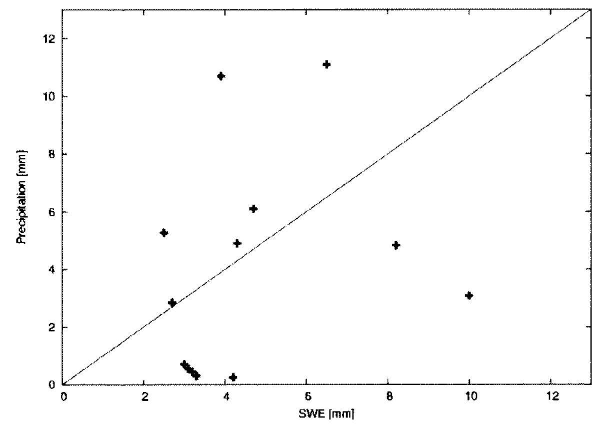

Fig. 5 Comparison between Precipitation and SWE increase

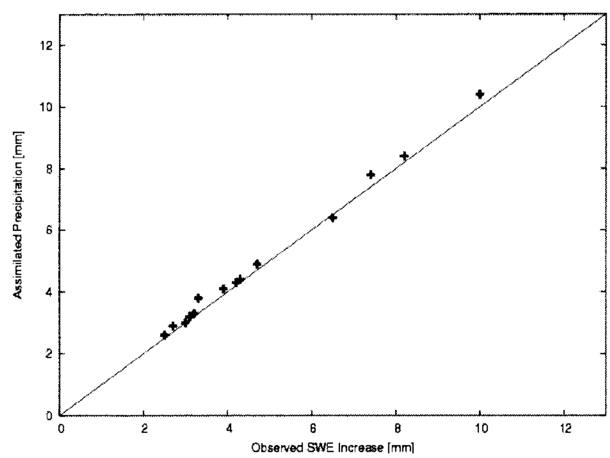

Fig. 6 Assimilated Precipitation

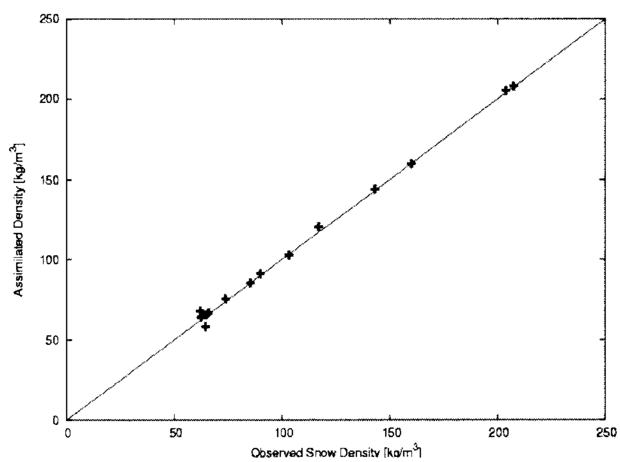

Fig. 7 Assimilated Density

4. Results & Discussion

In this paper a basic study was presented to develop an algorithm to correct snowfall observation from gauge measurements by coupling a radiative transfer and a snow model using data assimilation and passive microwave brightness temperature data at 89 GHz.

The assimilation results can be found in Fig. 6 and Fig. 7. Fig. 6 shows, that in all cases the assimilated precipitation agrees well with the observed increase of the snow water equivalent. Also the assimilated density agrees well with the observation as it can be seen in Fig. 7.

The average relative error in the case of the assimilated precipitation is 4.3%, for the assimilated density the error is 2.4%.

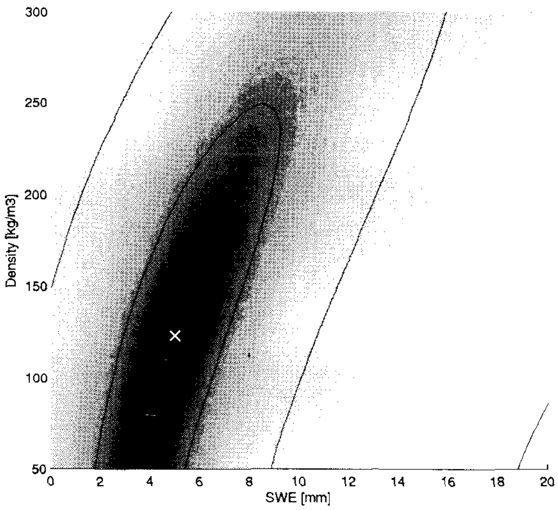

Fig. 8 Cost Surface for 1997-02-07

(1) Local or Global Minima?

As mentioned the results of the assimilation scheme are in good agreement with the observation. For this application only the 89 GHz channel with both the vertical and horizontal polarization is used. This raises the question if there is really only one optimal solution.

To evaluate whether or not only one unique solution exist, the cost surface for the case at 1997-02-07 was calculated. This was done by calculating all possible cost values for the density ($\rho_s \in [50,300]$ where $\Delta\rho=1$) and solid precipitation ($p \in [0.0,20]$ where $\Delta p=0.1$). The observation ($\rho=117.0$ kg/m^3 and $p=4.7$ mm) is marked with a white cross. The results of this simulation are presented in Fig. 8. This figure shows the cost function as a contour map, where dark areas are representing density and precipitation combinations, which are close to the optimum solution. It clearly shows, that only one global minima exist. Similar results were obtained by applying the same method to all presented cases.

(2) Satellite Data

For this study only modeled brightness temperature data was available. But the results of this study are showing the possiblity to use the brightness temperature observation at 89 GHz for snowfall observation.

A follow up study will be implemented to observe ground based brightness temperature data to validate the algorithm.

Also, if satellite based brightness temperature data is to be used. It will be necessary to evaluate the influence of the radiative transfer in the atmosphere on the observation at 89 GHz.

(3) Meteorological Model Output

A further source for solid precipitation data, is snowfall model output from meteorological models.

Meteorolgical model output data is available even for remote areas, where no gauge network can be found and in combination with observed satellite brightness temperature data it is possible to validate the model output and to provide an accurate snowfall product.

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