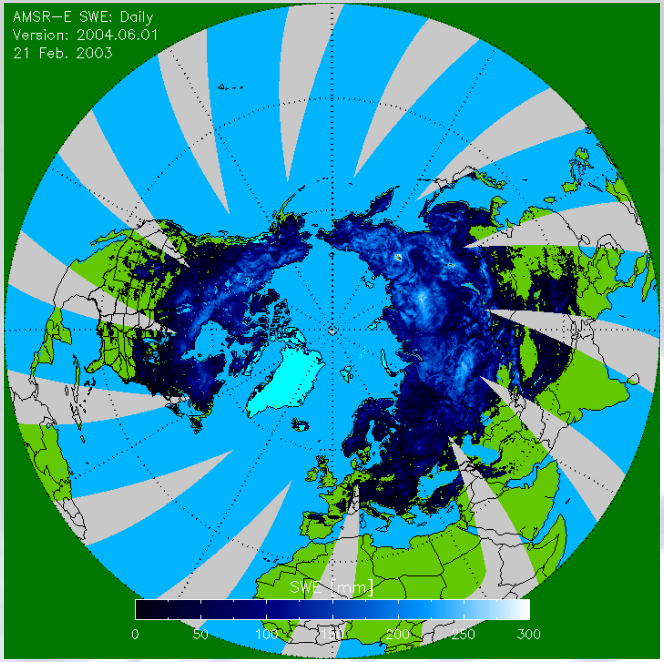
ASSESSING DYNAMIC APPROACHES IN SNOW WATER EQUVALENT/SNOW DEPTH RETRIEVAL FROM AMSR-E BRIGHTNESS TEMPERATURES

M. Tedesco[1,2,3], J. L Foster[2] and R. E. J. Kelly[4]
With the contribution of T. Markus[2], R. Reichle[2] and A. Loew[5]

1) City University of New York, USA
2) NASA Goddard Space Flight Center, USA
3) University of Maryland, Baltimore County, USA
4) University of Waterloo, Canada
5) University of Munich, Germany

MicroRad 2008 – Firenze - Italy

The AMSR-E Snow Water Equivalent



- In 2007, after long time a team has been selected from NASA for funding for maintaining and refining the AMSR-E SWE product:

PI – Tedesco M. (lead, CCNY, NASA)
co-PI – Kelly R. (Univ. Waterloo)

co-I's :
J. Foster (NASA)
E. J. Kim (NASA)
J. Wang (NASA)

Collaborators:
M. Hallikainen (Finland)
C. Derksen (Canada)

Support Specialist: J. Miller (RSIS)

$$SD_{cm} = FF * \frac{(A*(18V-36V))}{(1-FD*0.6)} + (1-FF)* [\ (A*(10V-36V)) + (B*(10V-18V))$$

Forest

Non-forest Shallow snow

Non-forest Deep snow

A = f(pol36), B= f(pol18)

AMSR-E SWE Product Roadmap

Implementation

Science development

Implementation of dynamic physically-based algorithm

Development/leveraging of field experiment data for validation efforts

atmospheric correction

Comparison of Approaches

Coupling of AMSR-E and Quikscat snow products

Coupling of AMSR-E and MODIS snow products

vegetation network model for vegetation correction

Snow energy balance model component

Involvement of EM models

Current algorithm

Simple empirical representation of R/T snow emission (Chang 1987-2003)

1995 2005 2006 2007 2008 2008-2009

Dynamic approaches on grain size growth

- In 2003 Kelly et al. proposed a dynamic approach considering an exponential growth model for grain size combined with an electromagnetic model (DMRT)
- Main hypothesis: snow grains grow along the snow season as an exponential function of the number of days (based on a work by Sturm)
- Results regarding its potential extension to large scale applications are reported here
- Also, results derived when using combined electromagnetic and land surface models driven with meteorological forcing data are reported
- These can support the conceptual development of radiance-based assimilation approaches

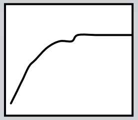
Tb Modeling

- Electromagnetic model → HUT

Inputs to the model are as follows:

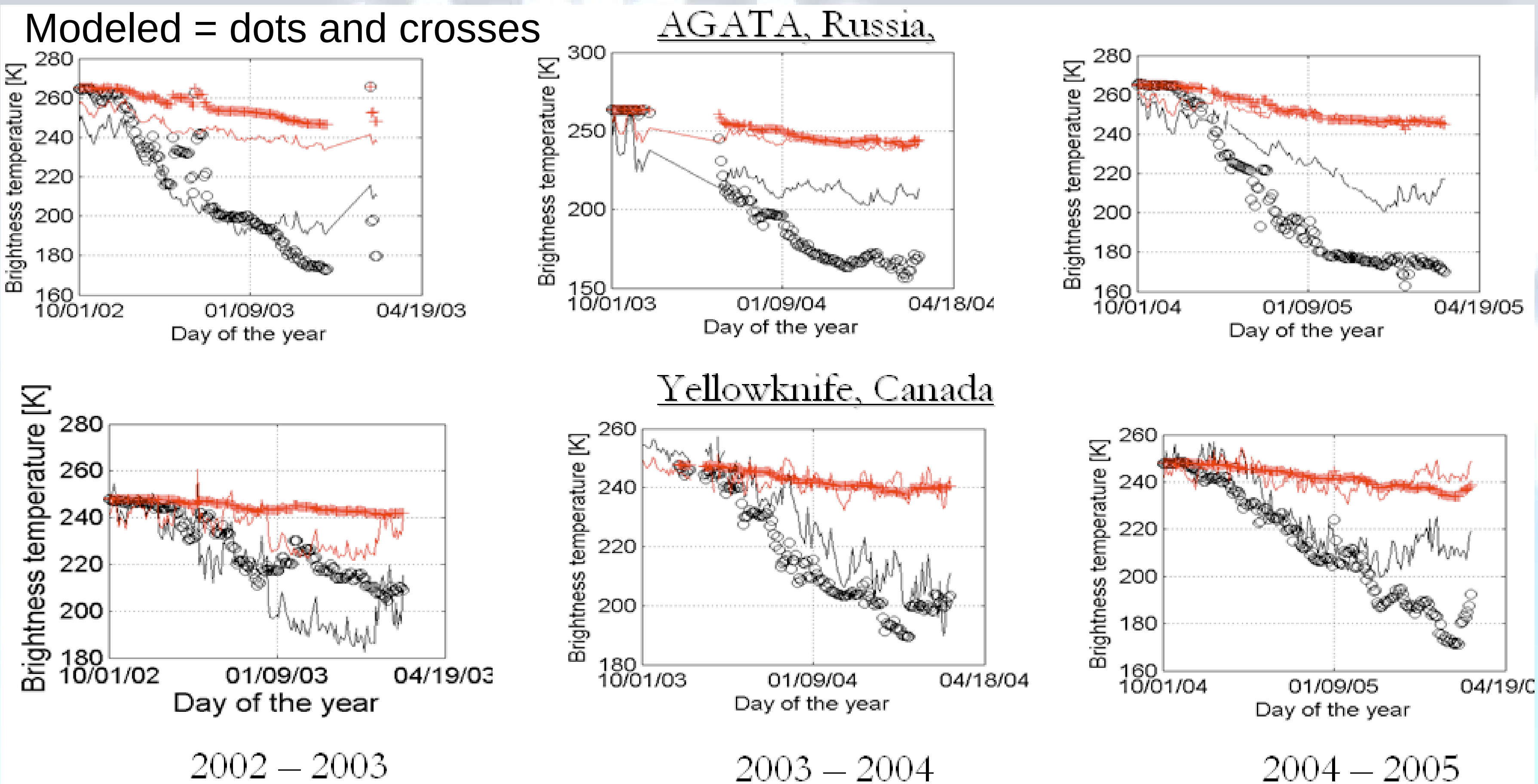
a) Snow depth from ground measurements

b) Grain size is derived from the exponential model and it is reduced when snow depth increase to account for the new snow

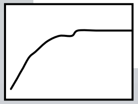


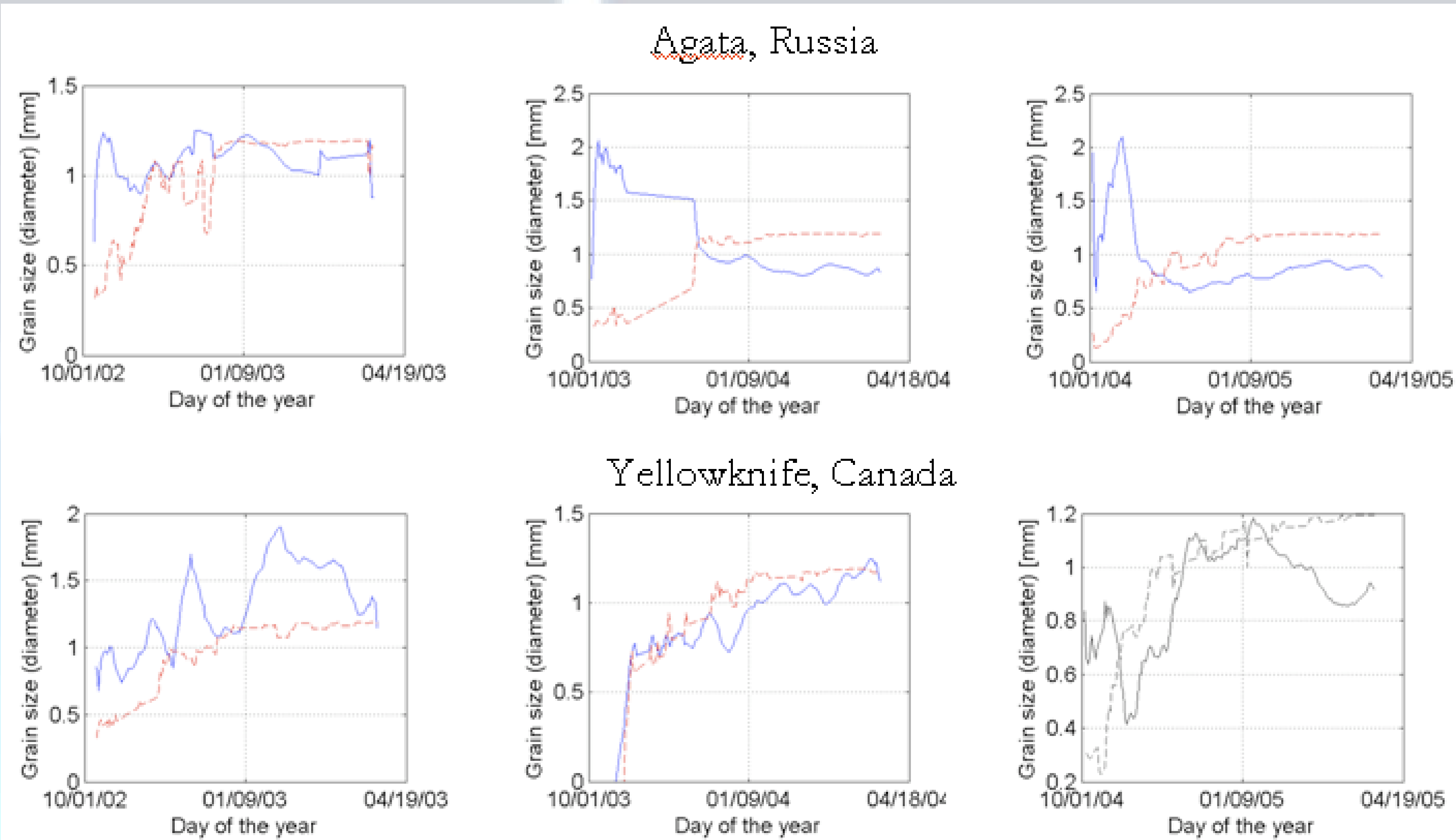
c) Density and soil temperature are kept fixed

d) Air/snow temperature is derived from ground measurements

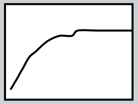


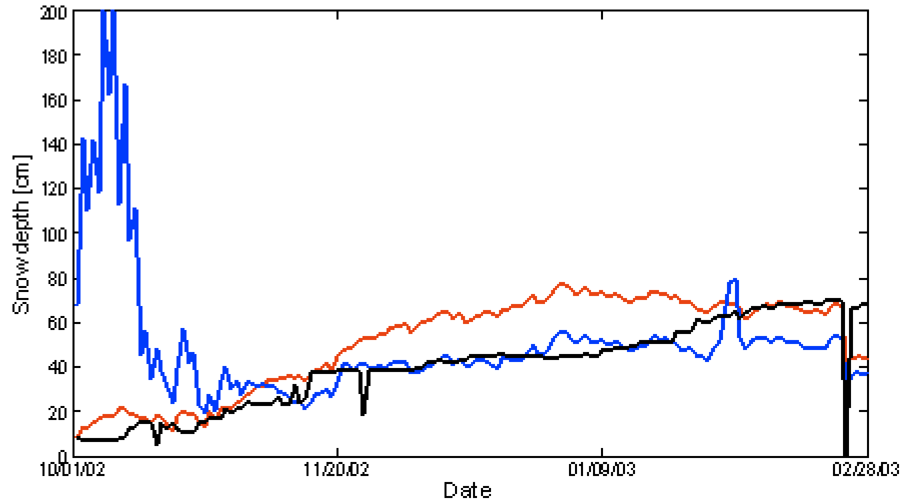
Comparison between exponential growth modeled (red) and optimum (blue) grain size values





Dynamic retrieved vs. static snow depth values

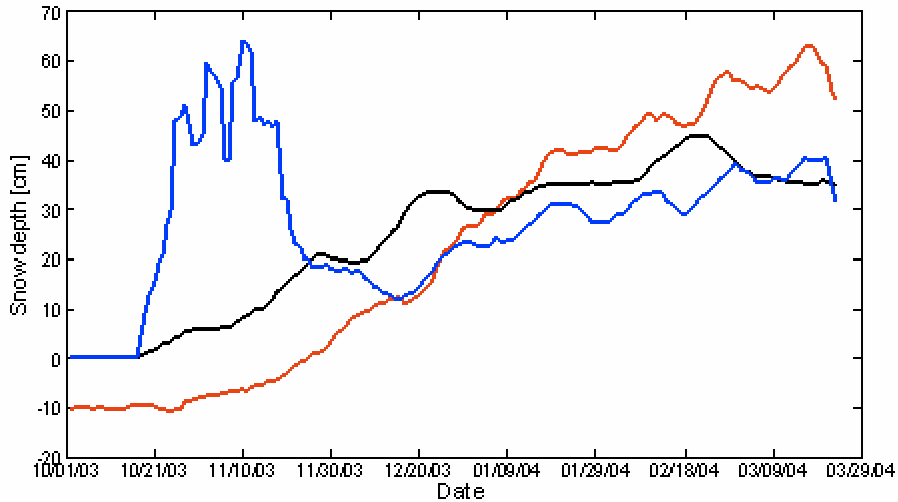




Agata, 2002

Blue = exponential model
Red = Chang’s algorithm
Black = ground data

Grain size is underestimated by the exp. model at the beginning of the season. This leads to an overestimation of snow depth.



Yellow, 2003

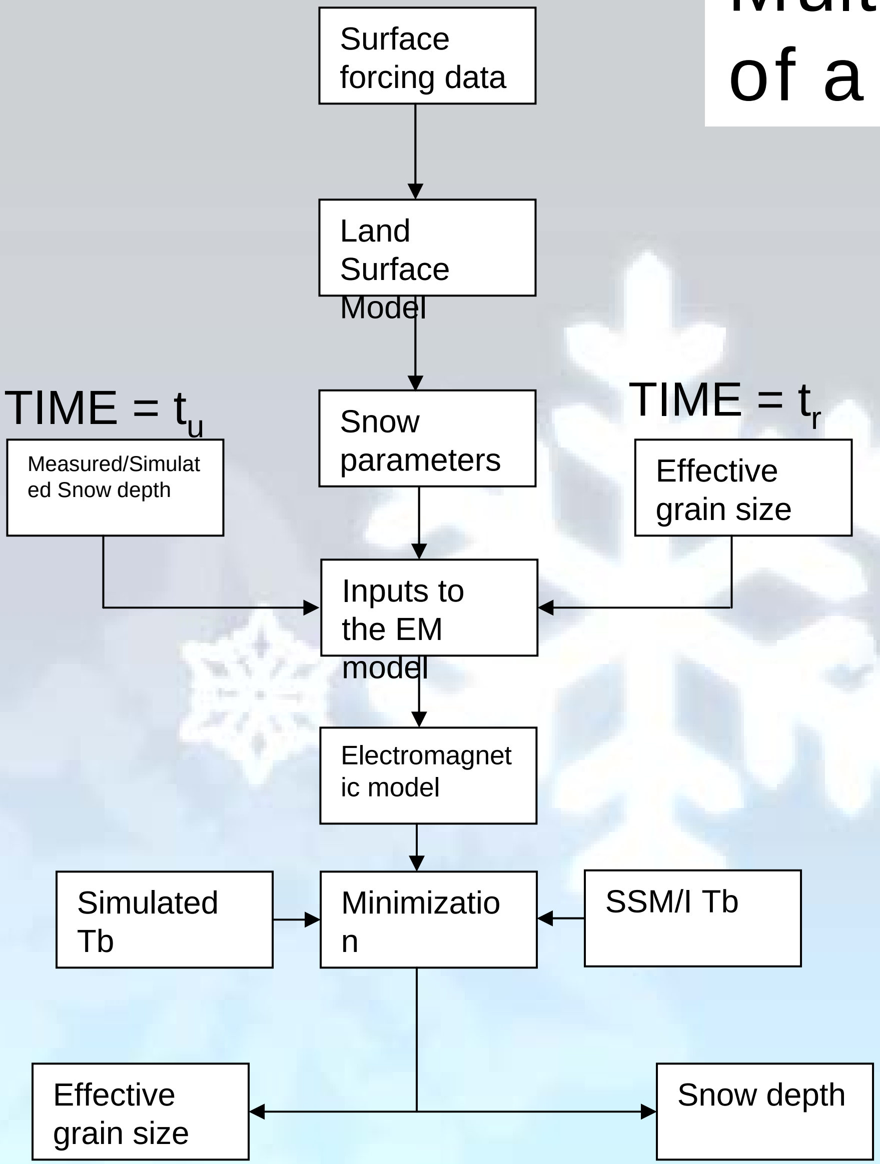
SMART

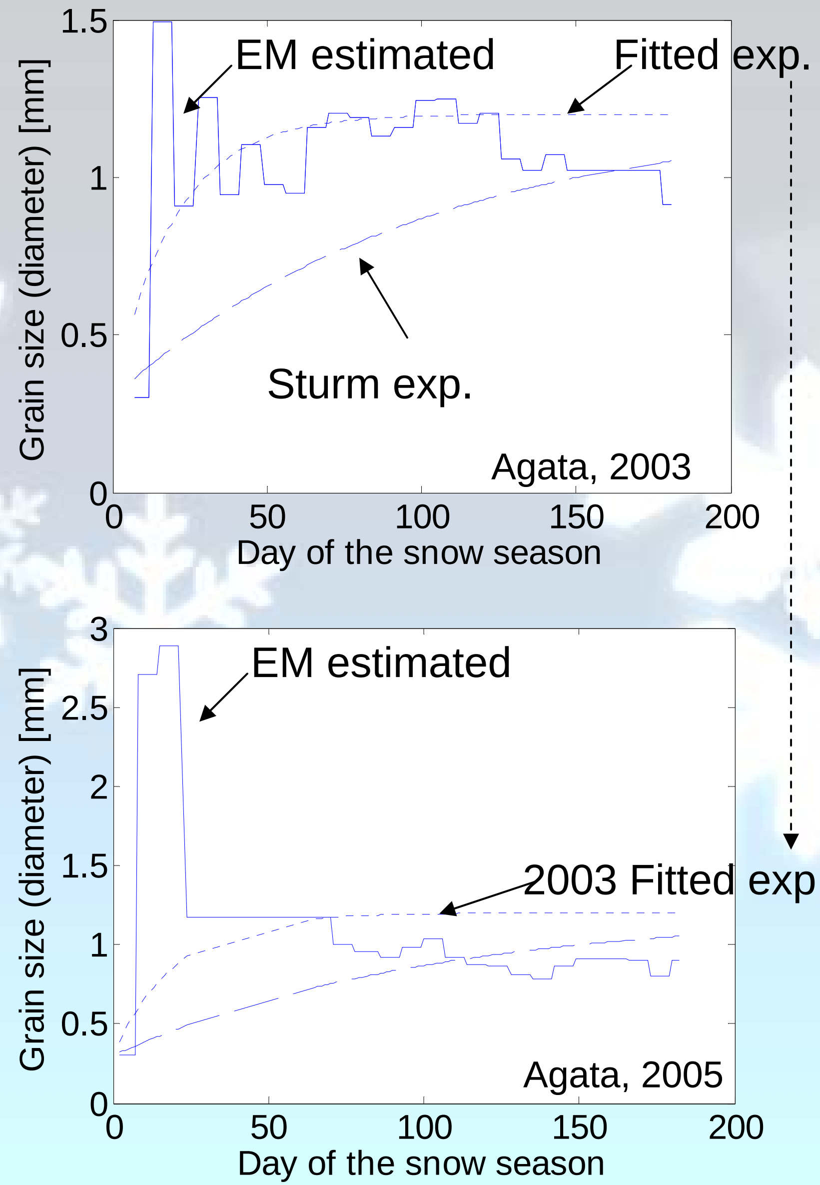
Snow Modelling Algorithm and Retrieval Tool

M. Tedesco, A. Löw, R. Reichle

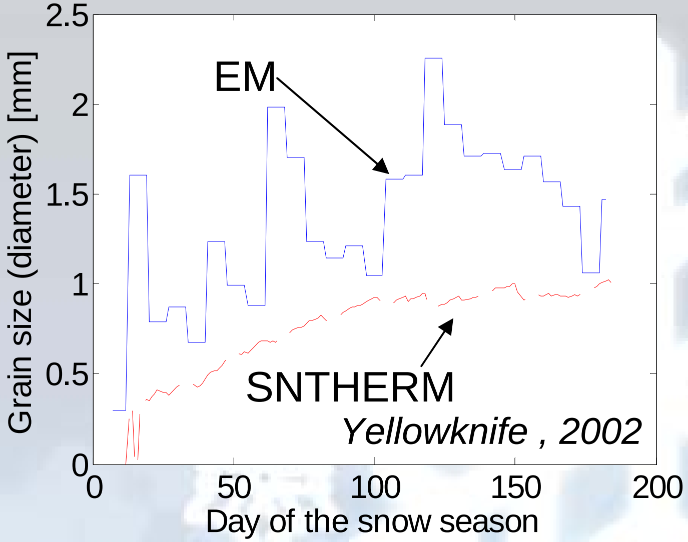
- Providing a tool for the improved retrieval of snow information using remote sensing data
- Coupling of different snow process models with remote sensing data using physically based radiative transfer models
- Providing a tool for the assimilation of snow information/satellite data into a physically based snow process model
- coded in Matlab/Fortran – under testing on 50 wmo stations worldwide
- Preliminary questions we are trying to answer: what is the expected behaviour of dynamic coefficients ? Can we reproduce this behaviour from information complementary to satellite data ? If so, how ?

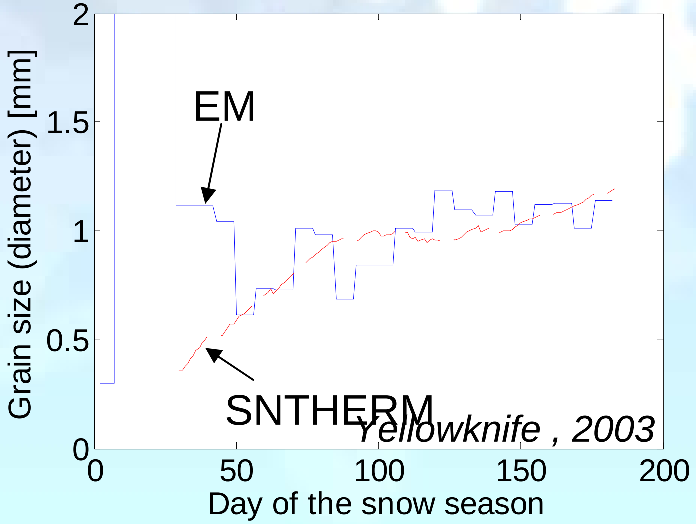
Multi-temporal ingestion of a priori information

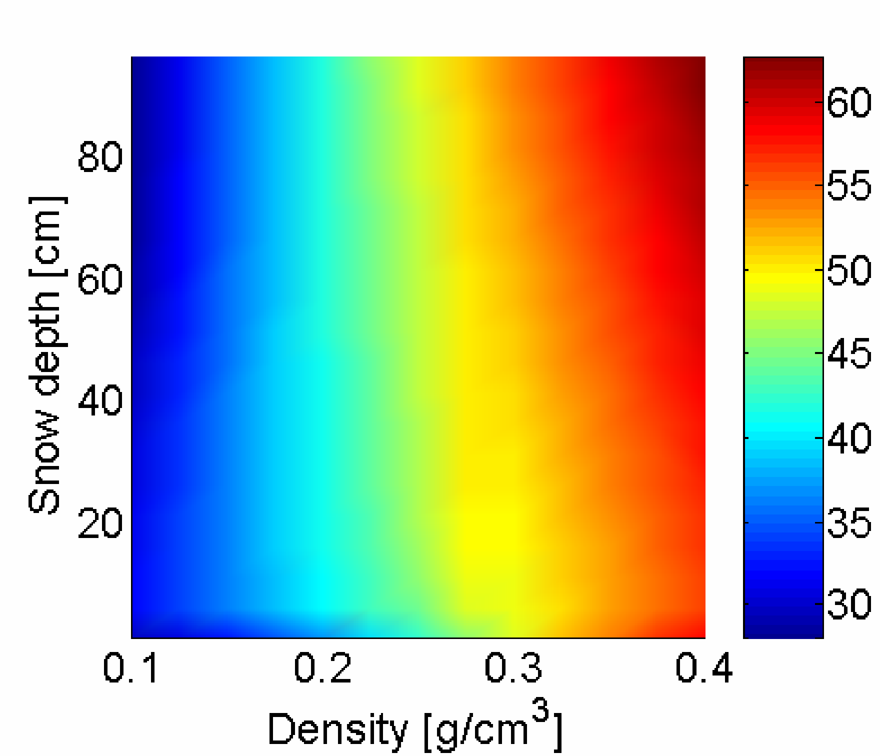




Comparison between EM-estimated and physically-based snow model outputs (SNTHERM)



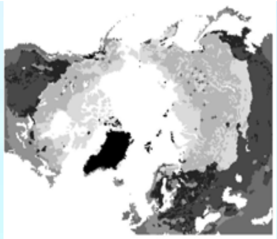




Percentage error (underestimation) between the snow depth values obtained using 1 mm in grain size matching the brightness temperatures obtained considering 0.75 mm.

Ingesting snow depth information: from the snapshot algorithm to a multi-temporal approach

				WMO		CLSM		CLSM	WMO
		Chang	Foster	Dynamic	Mod. Static	Dynamic	Mod. Static	HUT	HUT
RMSE [m]	1	0.57	0.52	0.07	0.1	0.17	0.18	0.39	0.16
	2	0.54	0.50	0.05	0.07	0.12	0.13	0.49	0.13
	3	0.53	0.48	0.06	0.08	0.15	0.15	0.45	0.16
Percentage error [%]	1	58.6	55.4	5.1	5.5	63.6	57.5	47.2	7.1
	2	62	58.9	6	7	49.2	44.3	59.3	8.8
	3	58.4	55.8	5	9.5	59	47.7	58.2	10.6
Correlation	1	0.51	0.45	0.77	0.51	0.73	0.51	0.54	0.6
	2	0.64	0.56	0.82	0.64	0.75	0.64	0.49	0.7
	3	0.84	0.78	0.87	0.84	0.77	0.84	0.58	0.7



Statistics are based on 3 years (2001,2002,2003) data over 49 stations

Conclusions

- The current AMSR-E algorithm, delivered on Sept. 2005, makes use of a dynamic approach though still conservative
- Factors such as vegetation, atmospheric effects and potential improvement deriving form multi-sensor approach have been (are being) evaluated
- Grain size modeling is a key aspect for development of future dynamic approaches, especially in view of radiance-based assimilation techniques
- Both simplified and physically-based models cannot consistently reproduce the size of EM effective scatterers, significantly affecting the error on snow depth/SWE retrieval
- Ingesting a-priori information on snow depth/SWE at given time-steps (e.g. from snow model) considerably improves the retrieval (multi-temporal approach instead of snapshot algorithm)

Preliminary analysis at large spatial scale

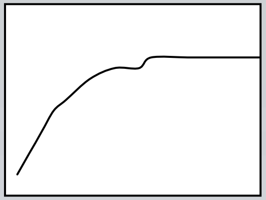
Baseline
Snow depth
error statistics

1.6(18v-36v)/(1-0.2ff)	2002 RMSE	2002 Bias	2003 RMSE	2003 Bias
All Data	**24.01**	**6.49**	**24.37**	**6.07**
FF = 0%	24.63	11.32	26.19	5.68
0% < FF < 50%	24.60	4.38	23.96	7.05
FF > 50%	16.82	0.15	18.03	-1.10

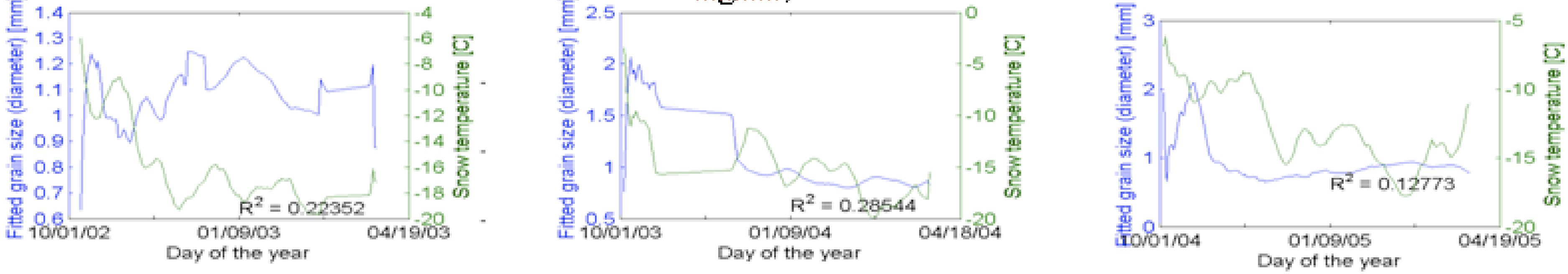
New method
Snow depth
error statistics

New Algo (Pol >=3)	2002 RMSE	2002 Bias	2003 RMSE	2003 Bias
All Data	**21.83**	**-1.04**	**22.35**	**-2.43**
FF = 0%	21.41	0.78	24.01	-4.57
0% < FF < 50%	22.76	-2.49	21.84	-1.25
FF > 50%	16.45	1.62	17.31	-2.41

Relationship between optimum grain size and surface temperature evolution



Agata, Russia



Yellowknife, Canada