A New Snow Cover Product Based on Multi-Sensor Multi-Temporal Satellite Data

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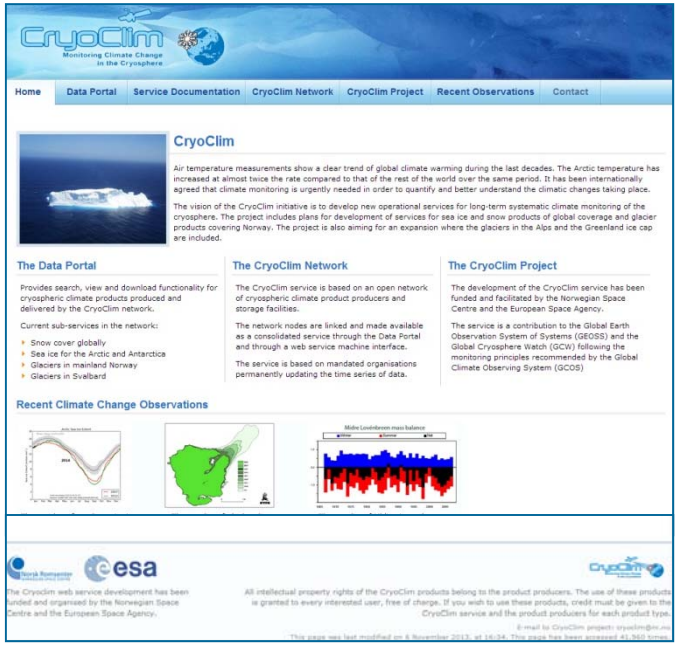
Monitoring Climate Change in the Cryosphere

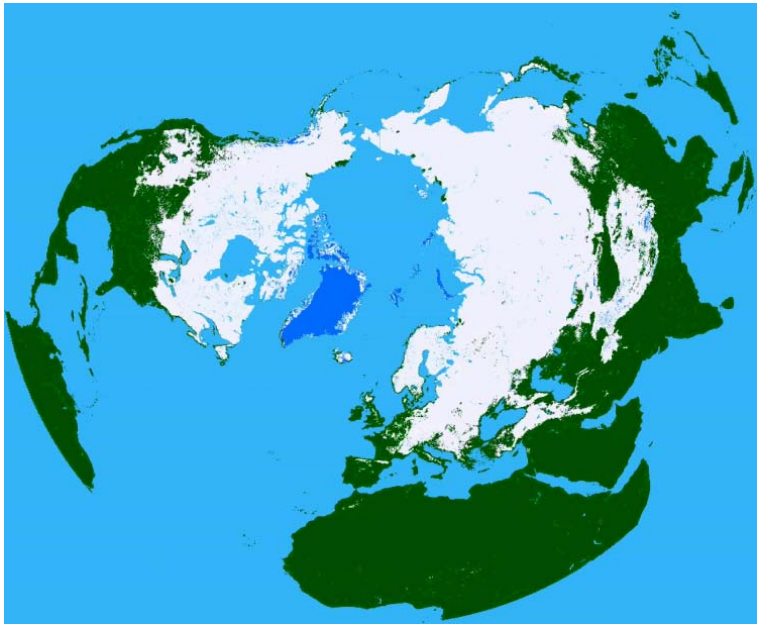
The CryoClim service

- The CryoClim project (2008-2013) initiated by the Norwegian Space Centre (NSC) and administrated by ESA ESTEC under the PRODEX programme developed algorithms, products and a service for cryospheric climate monitoring
- Operational service from November 2013: www.cryoclim.net
- Products:
  - Sea ice (MET): 1979-present, global
    - Sea ice concentration (SIC)
    - Sea ice edge (SIE)
  - Snow cover (MET/NR): 1982-present, global
    - Snow cover extent (SCE)
  - Glaciers Norway (NVE): 1952/1988–present
    - Glacier area outline (GAO)
    - Glacier lake outline (GLO)
    - Glacier lake outburst flood (GLOF)
    - Glacier periodic photo series (GPP)
  - Glaciers Svalbard (NPI): 1936/1992–present
    - Glacier area outline (GAO)
    - Glacier surface type (GST)
  - Extended with Greenland in 2014 (GEUS): 2000-present
    - Glacier surface type (GST)



Sub-service snow

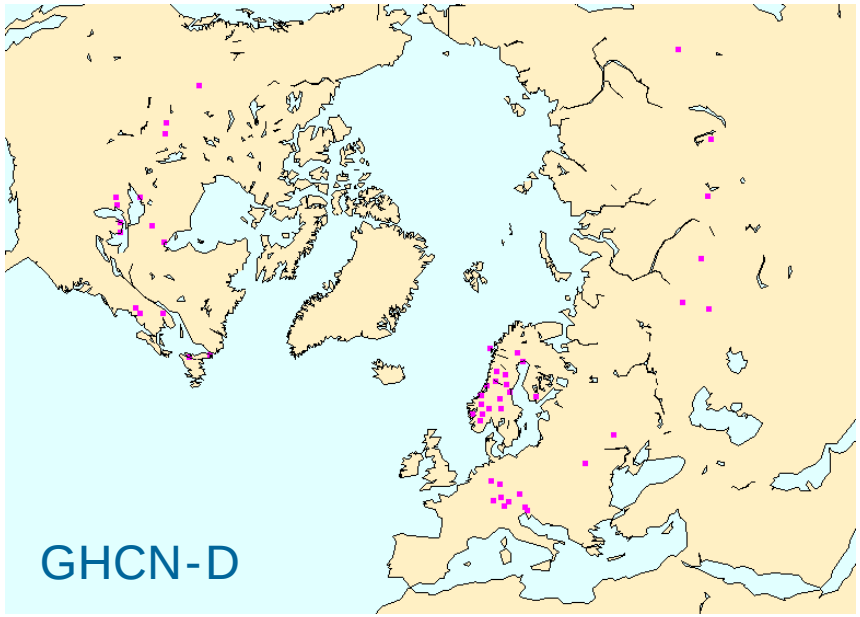
- Snow Cover Extent (SCE) (snow/no snow)
- Developed three “competing” prototype products:
  - SCE from PMR (10 km)
    - Based on SMMR (1978-1987) and SSM/I (1987-present)
  - SCE from optical (5 km)
    - Based on AVHRR GAC (1982-present)
  - SCE multi-sensor/temporal (5 km)
    - Combination of optical and PMR
- Final product: “Multi” product global time series 1982–present
- Aggregation levels: Day, month, year
- Projection/files: EASE-Grid, NetCDF CF, Northern & Southern Hemisphere
- Climate-change indicator products: Snow season length, first and last day of snow

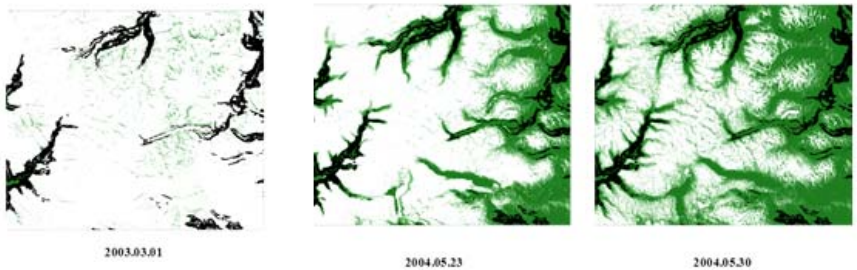


Multi-sensor multi-temporal snow cover 1 March 2005

Validation data

- Snow depth from the Global Historical Climatology Network Daily (GHCN-D) SYNOP database
- Filtered out stations with suspicious behaviour, taking into consideration that zero snow depth is not reported explicitly
- Set of snow reference maps based on Landsat (Scandinavia only)





Snow maps from Landsat TM/ETM+

The PMR SCE algorithm is based on an estimate of the probability of snow

$$P(S_k|x_1, x_2, \dots, x_n) = \frac{P(x_1|S_k) \cdot P(x_2|S_k) \cdots P(x_n|S_k) \cdot P(S_k)}{\sum_{m=1}^{C} P(x_1|S_m) \cdot P(x_2|S_m) \cdots P(x_n|S_m) \cdot P(S_m)}$$

SMMR

Snow classes:

Snow & no snow

Features:

x1=T18v-T37v

x2=T18h-T37h

SSM/I

Snow classes:

Dry snow, wet snow, no snow & no snow with a large portion of water

Features:

x1=T37v-T37h

x2=T19v-T37v

x3=T22v-T85v

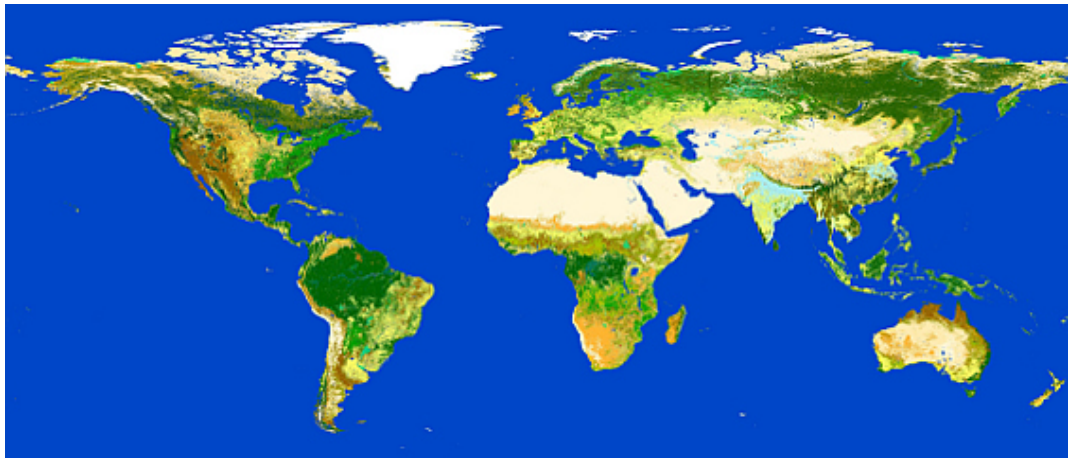
x5=T22v

x4=(1.95·T19v-0.95·T19h)/0.95

To mitigate the influence from ground cover/vegetation, we stratify the snow cover estimation to similar land cover

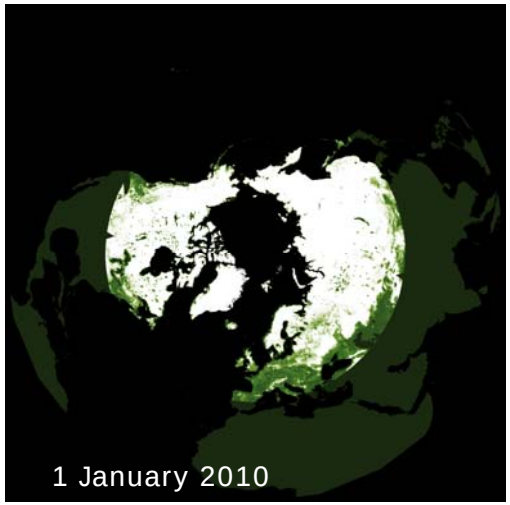
SMMR:
11 land cover groups

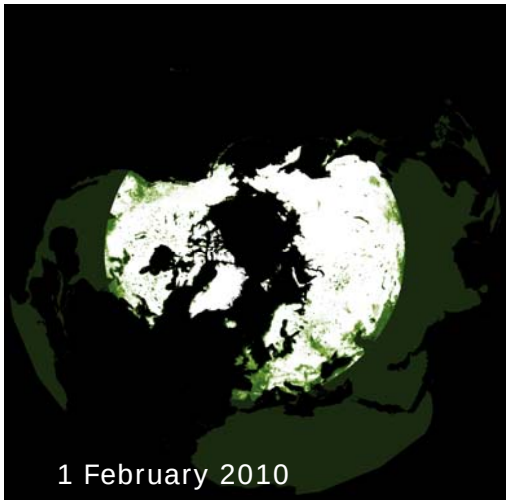
SSM/I:
7 land cover groups

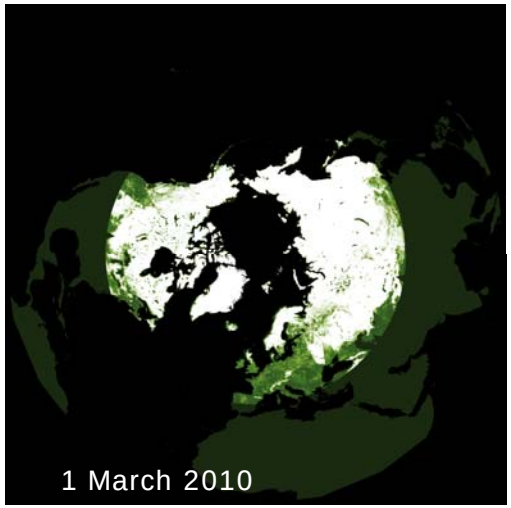


Land cover groups based on the ESA GlobCover product

Example snow cover maps







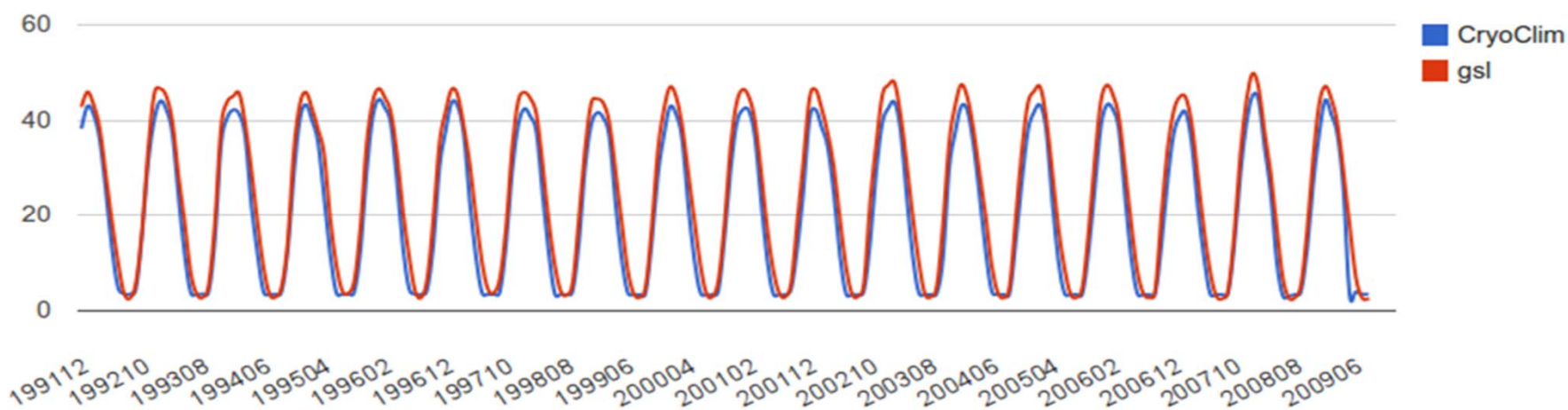
Algorithm performance

SMMR:

- Probability of correctly classified snow covered samples: **72%**
- Probability of correctly classified no-snow covered samples: **95%**

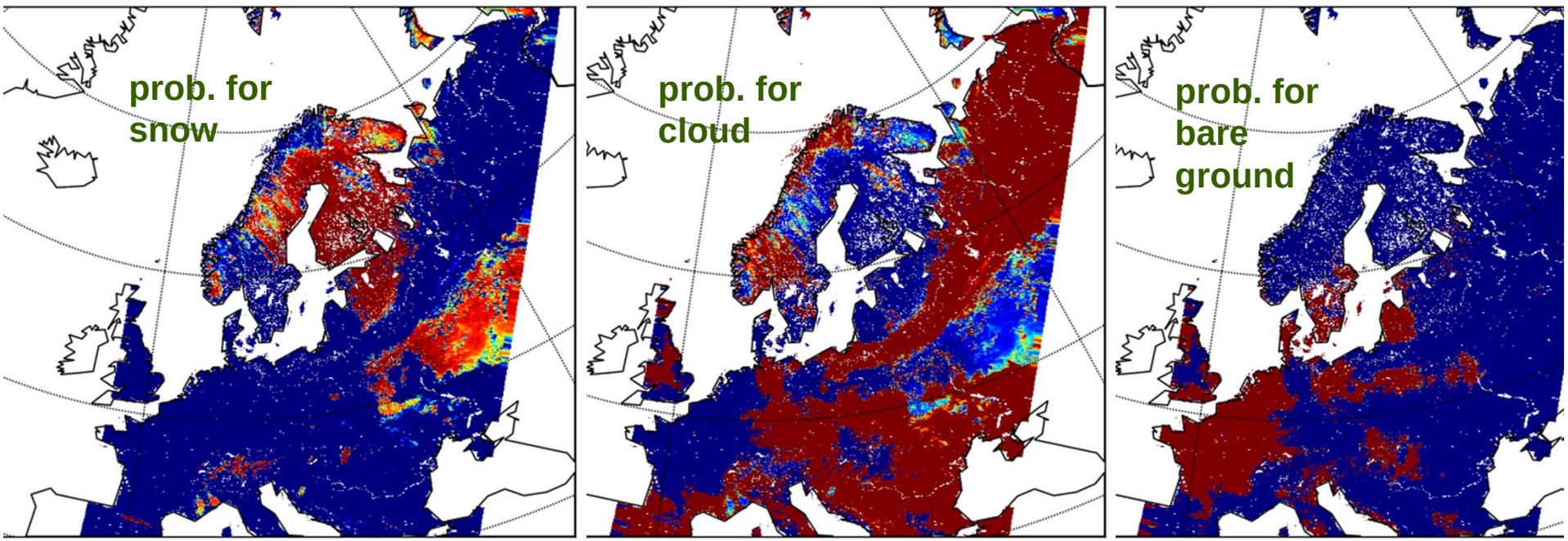
SSM/I:

- Probability of correctly classified snow covered samples: **86%**
- Probability of correctly classified no-snow covered samples: **86%**

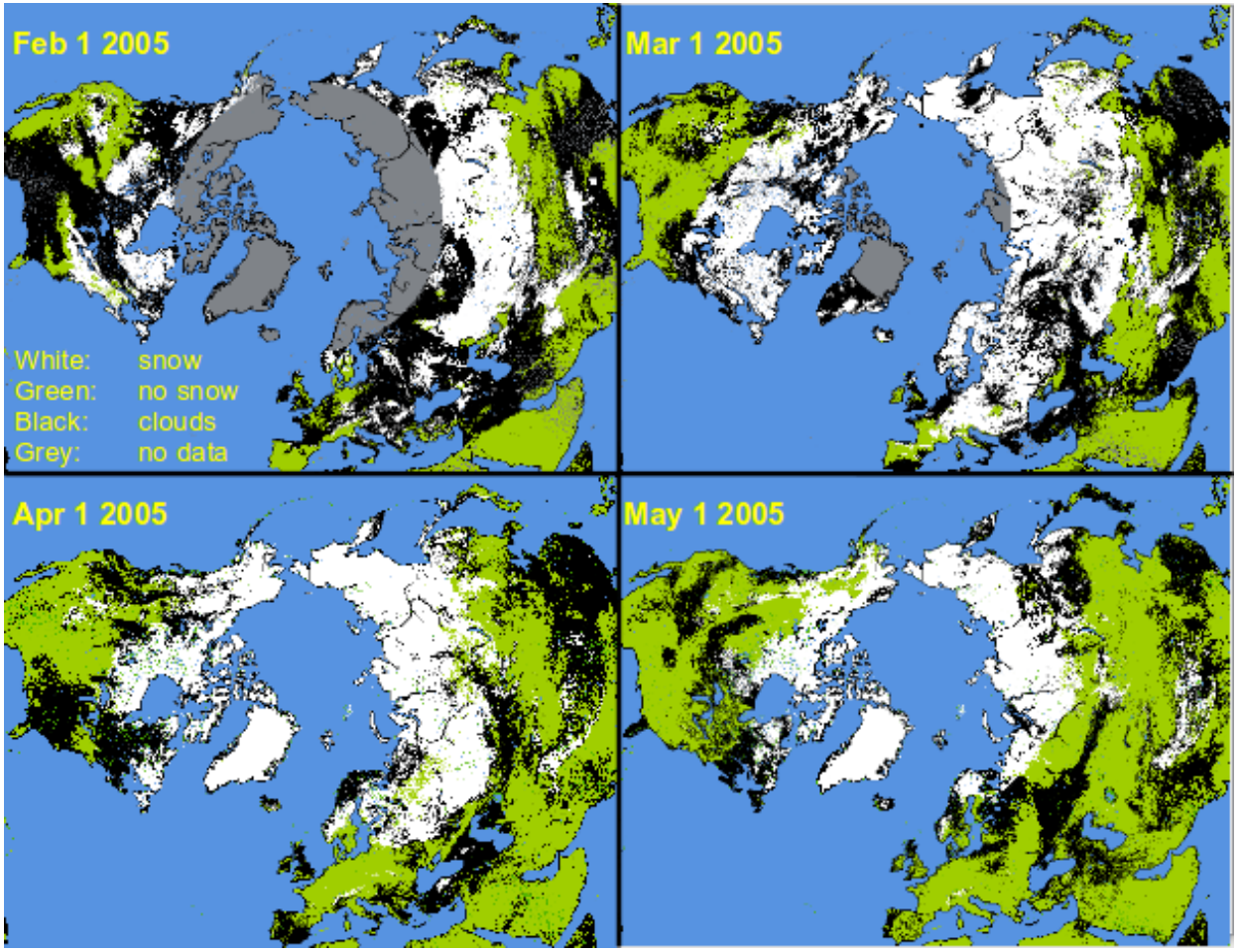


The optical AVHRR GAC SCE algorithm is based on an estimate of probability of snow

$$P(S_k|x_1, x_2, \dots, x_n) = \frac{P(x_1|S_k) \cdot P(x_2|S_k) \cdots P(x_n|S_k) \cdot P(S_k)}{\sum_{m=1}^{C} P(x_1|S_m) \cdot P(x_2|S_m) \cdots P(x_n|S_m) \cdot P(S_m)}$$



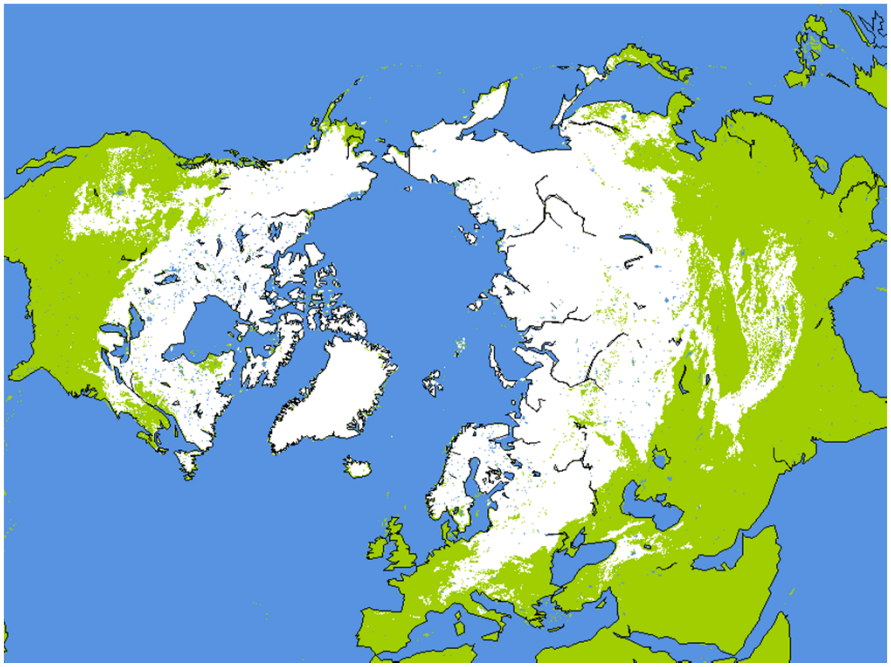
Optical SCE validation



Month	Hit	Miss	Total
200501	93%	7%	446
200502	97%	3%	650
200503	96%	4%	755
200504	88%	12%	604
200505	96%	4%	810
200506	99%	1%	1024
200507	100%	0%	1159
200508	100%	0%	1012
200509	100%	0%	900
200510	100%	0%	671
200511	94%	6%	232
200512	90%	10%	284
Sum 2005	**97%**	**3%**	**8547**

How would a pure multi-sensor approach work?

- A ‘straightforward’ approach would be a Bayesian combination of optical + PMR features
- This approach is ‘memory less’ of the past

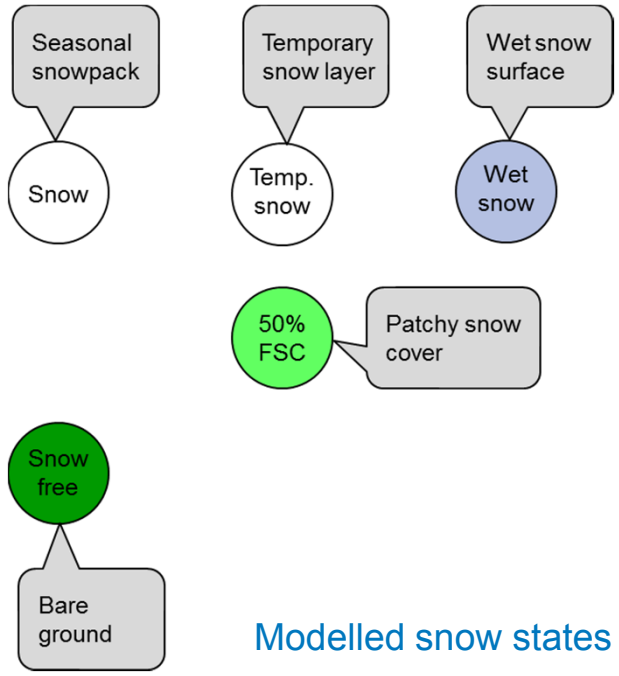


Multi-sensor AVHRR + SSM/I product for 15 March 2005

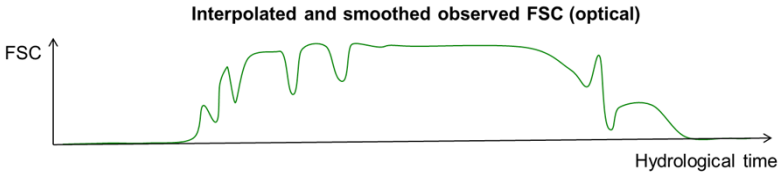
$$P(S_k|x_1, x_2, \dots, x_n) = \frac{P(x_1|S_k) \cdot P(x_2|S_k) \cdots P(x_n|S_k) \cdot P(S_k)}{\sum_{m=1}^{C} P(x_1|S_m) \cdot P(x_2|S_m) \cdots P(x_n|S_m) \cdot P(S_m)}$$

Multi-sensor multi-temporal optical + PMR

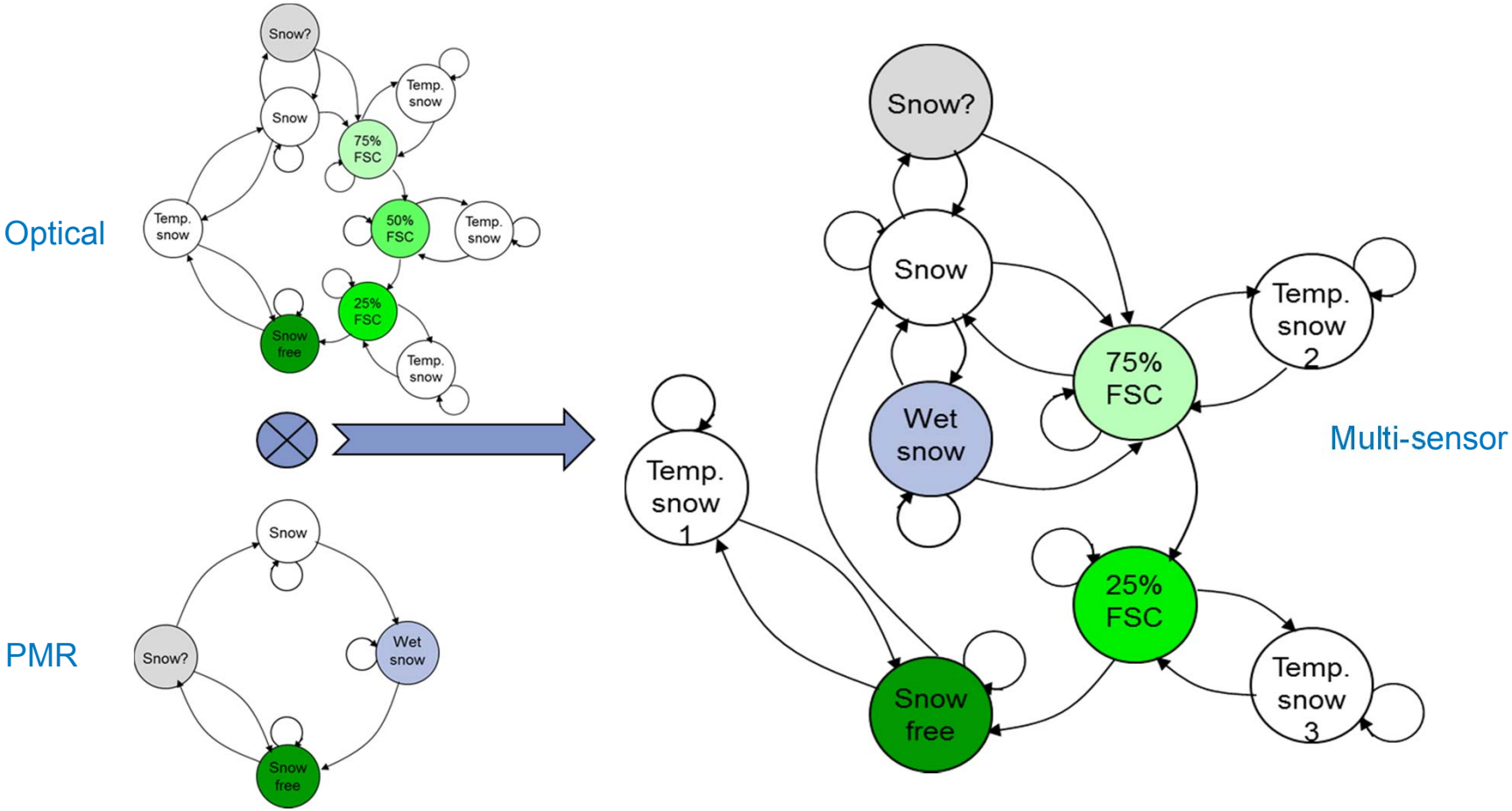
- The vision was to combine the best from optical and PMR:
  - Optical hampered by clouds and limited to daylight, but otherwise very accurate except for dense forests
  - PMR hampered by shallow snow depth and wet snow, but otherwise reliable and independent of daylight
- We have knowledge about the development of the seasonal snowpack; calling for multi-temporal approach:
  - Snow season start-up: Fluctuations between snow and bare ground
  - Winter season: Accumulation with snowpack present
  - Spring season: Gradual snowmelt with advent of patchy snow cover and temporal snow events



Modelled snow states



A state model based on fusion of single-sensor state models



Implemented the model applying the Hidden Markov Model framework

- In HMM we observe a system assumed to evolve through a series of different states
- Transitions from one state to another happen with certain probabilities
- While in a given state the system will produce observables with a certain probability density

States: $Q = \{S_1, S_2, \dots, S_v\}$

Observables: $\bar{X}^T = \{X^1, X^2, \dots, X^T\}$

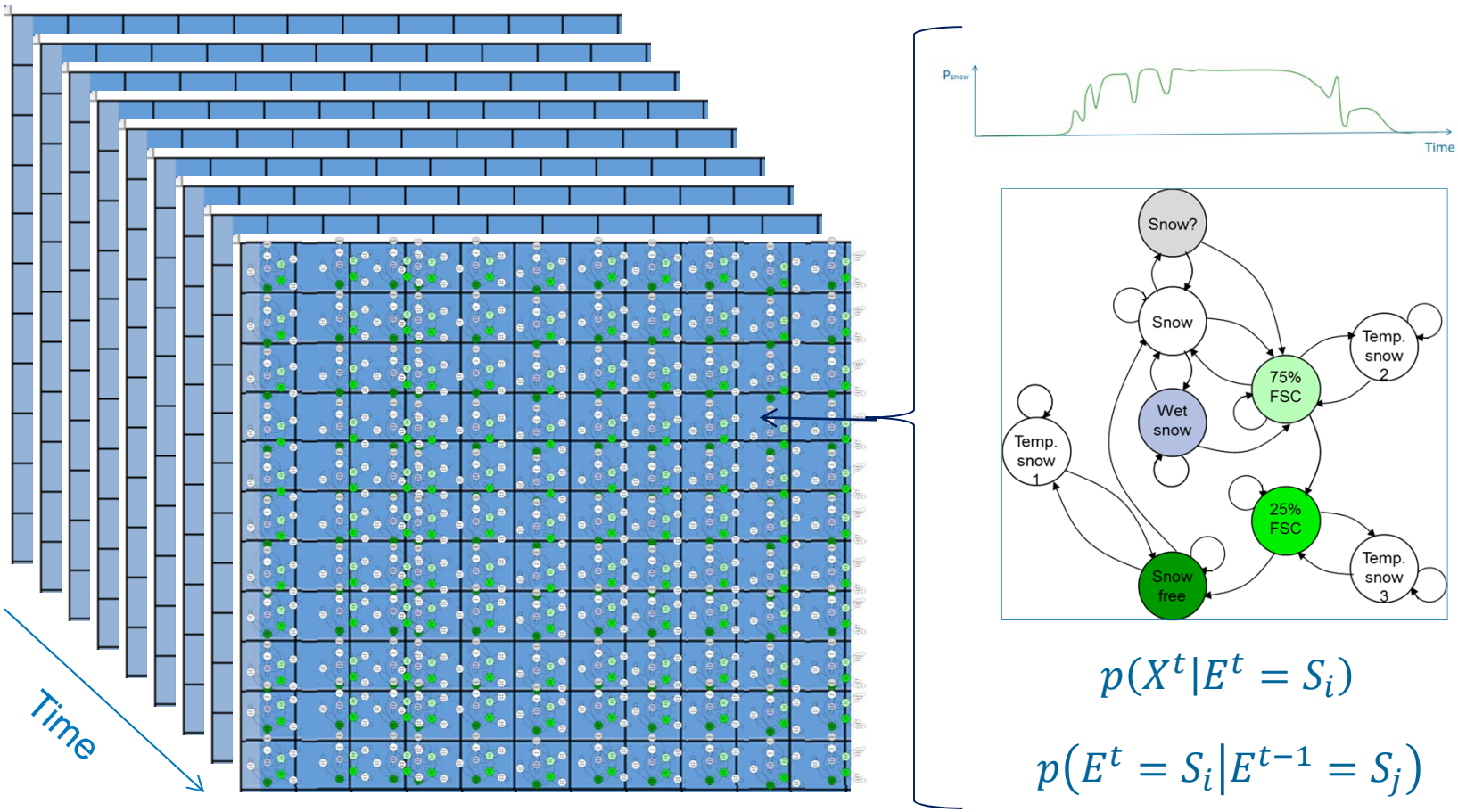
Prob. distr.: $p(X^t | E^t = S_i), i = 1, 2, \dots, v$

Transition probabilities.:

$$p\left(E^t = S_i \middle| E^{t-1} = S_j\right), i, j = 1, 2, \dots, v$$

Initial conditions: $p(E^1 = S_i), i = 1, 2, \dots, v$

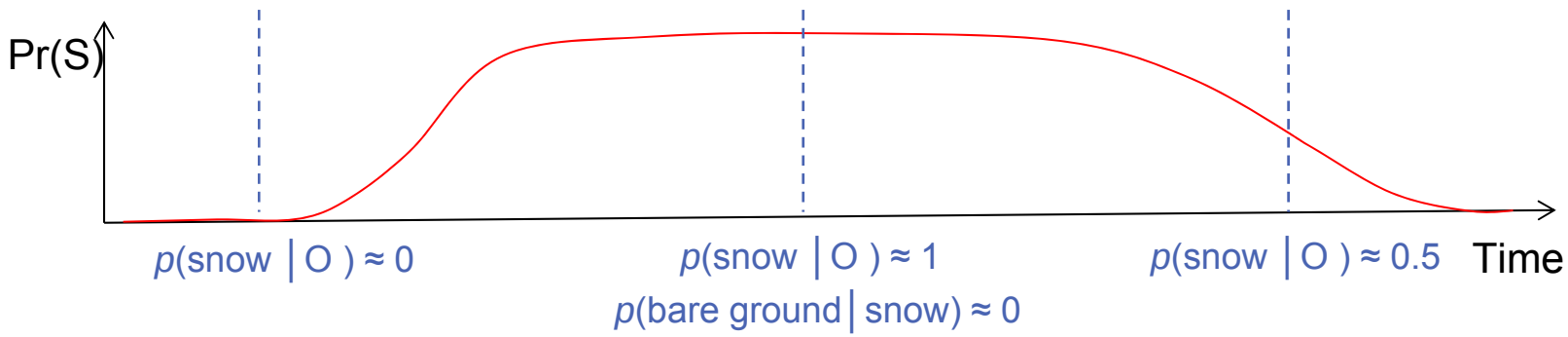
Note that a there is one state model per grid cell



$$p(X^t | E^t = S_i)$$

$$p(E^t = S_i | E^{t-1} = S_j)$$

Estimating the probabilities



Climatological probability of snow

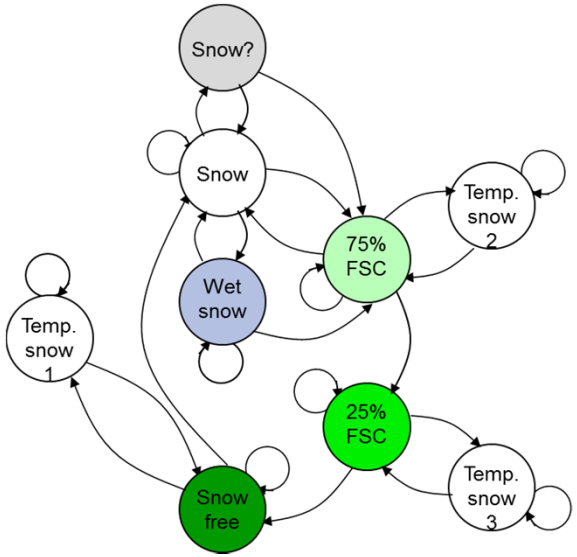
- Per grid cell daily climatological probability of snow computed from Savitzky-Golay smoothed PMR snow probabilities
- Used to estimate transition probabilities

Using the Viterbi algorithm to determine the model sequence best explaining the temporal observations

- The Viterbi algorithm is a dynamic-programming algorithm for finding the most likely sequence of hidden states (the Viterbi path) that result in a sequence of the observables
- The algorithm requires as input the state probability density functions, the transition probabilities between the different states and the initial probability of each state

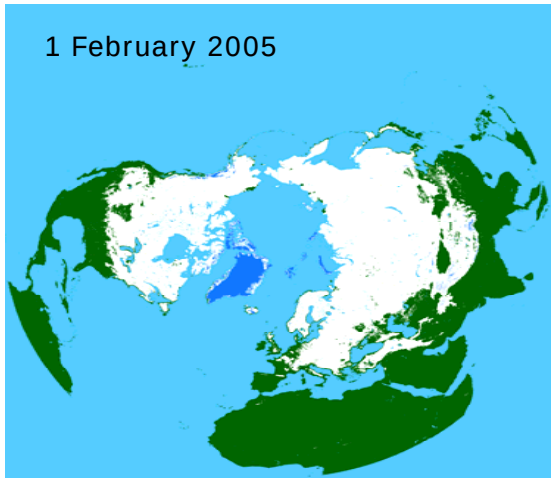
$$V_{1,k} = p(X^1|k)p(E^1 = S_k)$$

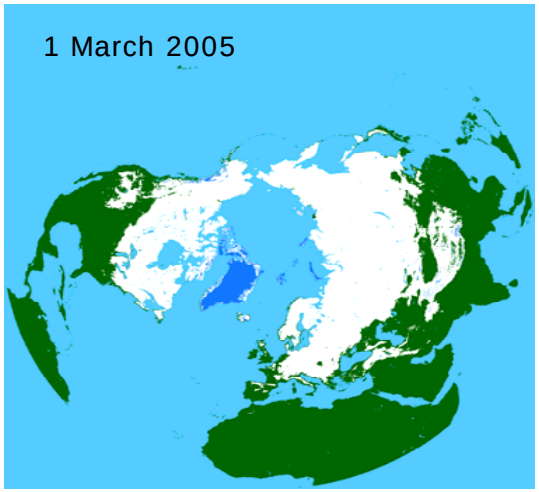
$$V_{t,k} = p(X^t|k)\max_i\left(p\left(E^t = S_i \middle| E^{t-1} = S_j\right)V_{t-1,k}\right)$$

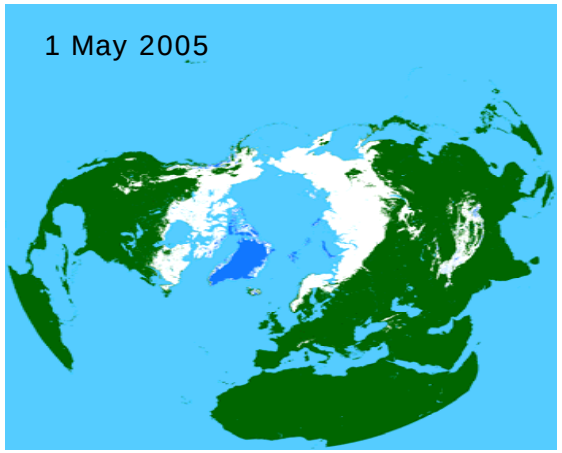


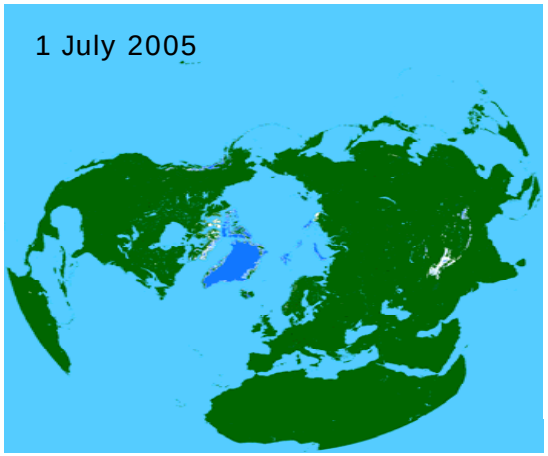
Final state model chosen

Examples







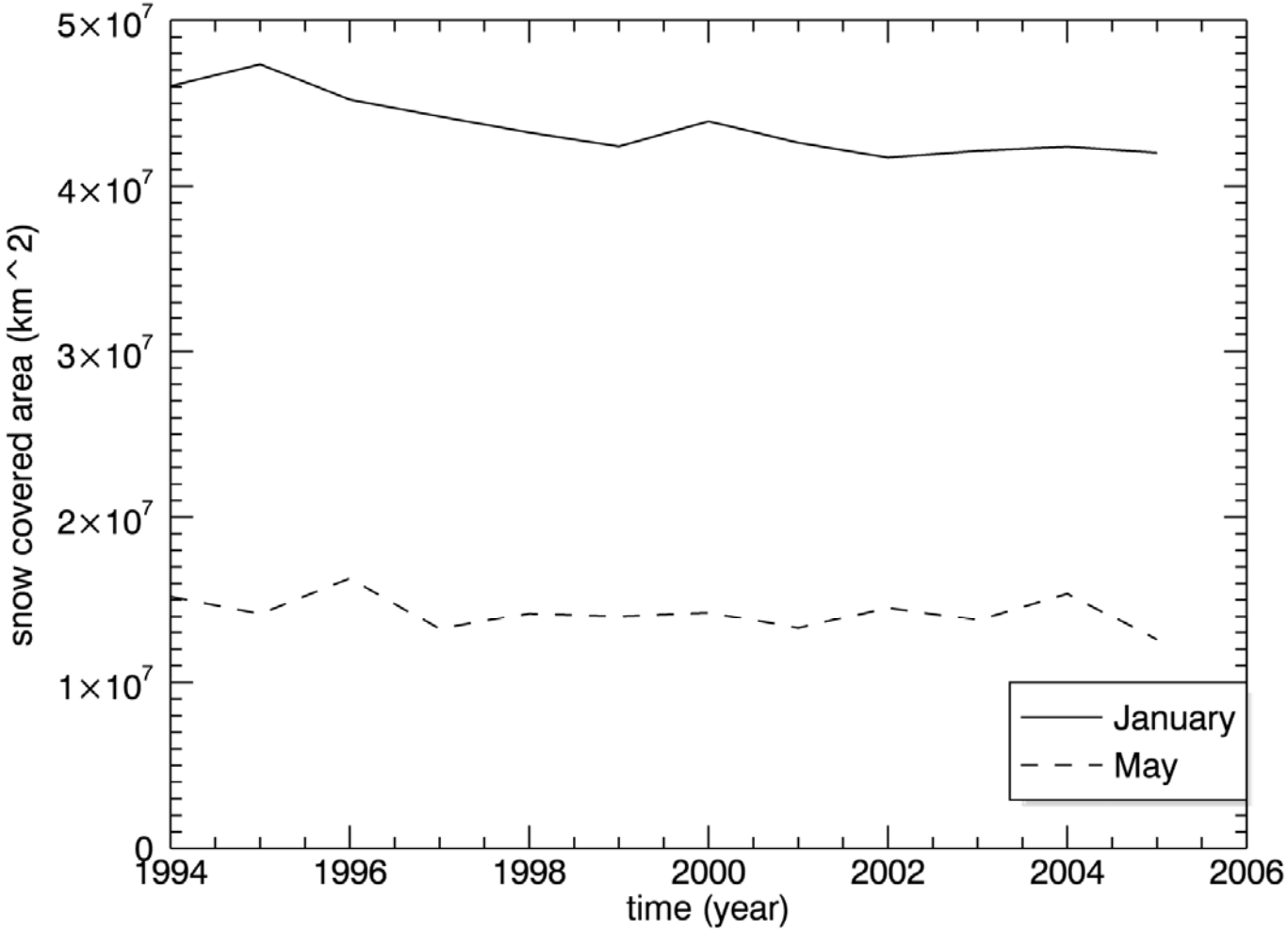


Examples and validation results

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
True	0.82	0.90	0.94	0.88	0.93	0.99	1.00	1.00	1.00	0.98	0.78	0.76
False	0.18	0.10	0.06	0.12	0.07	0.01	0.00	0.00	0.00	0.02	0.22	0.24
Total pixels	1298	1318	1385	1008	1254	1437	1488	1488	1427	1225	702	1170

Overall accuracy: 92.4 %

Development for January and May 1994-2005 based on monthly NH products

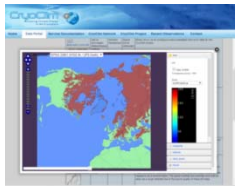


Conclusions and further work

- Developed a multi-sensor time-series optical + PMR fusion algorithm for estimation of Snow Cover Extent (SCE) based on a Hidden Markov Model approach
- Key requirement: Observational product; not modelled product
- Overall accuracy 92.4%, polar night and clouds avoided
- Version 1.0 product time series (1982-present) is to be completed in the autumn
- Version 2.0 with improvements planned to be released in 2015

Planned improvements:

- Improved training:
  - Snow along coastlines
  - Overestimation in the Tibetan Plateau?
- Extending validation with new data:
  - Former Soviet Union HSDSD and FSUHSS datasets
  - VHR and HR snow maps
  - Product intercomparison
- New additions:
  - Per-grid-cell uncertainty
  - Trend analysis
  - Indicator products



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