snow cci

New 38-Year Time Series of Daily, Global Fractional Snow Cover Maps

Rune Solberg, Øystein Rudjord and Arnt-Børre Salberg, NR[1]
Mari Anne Killie, Steinar Eastwood and Atle Sørensen, MET[2]
Carlo Marin and Valentina Premier, EURAC[3]

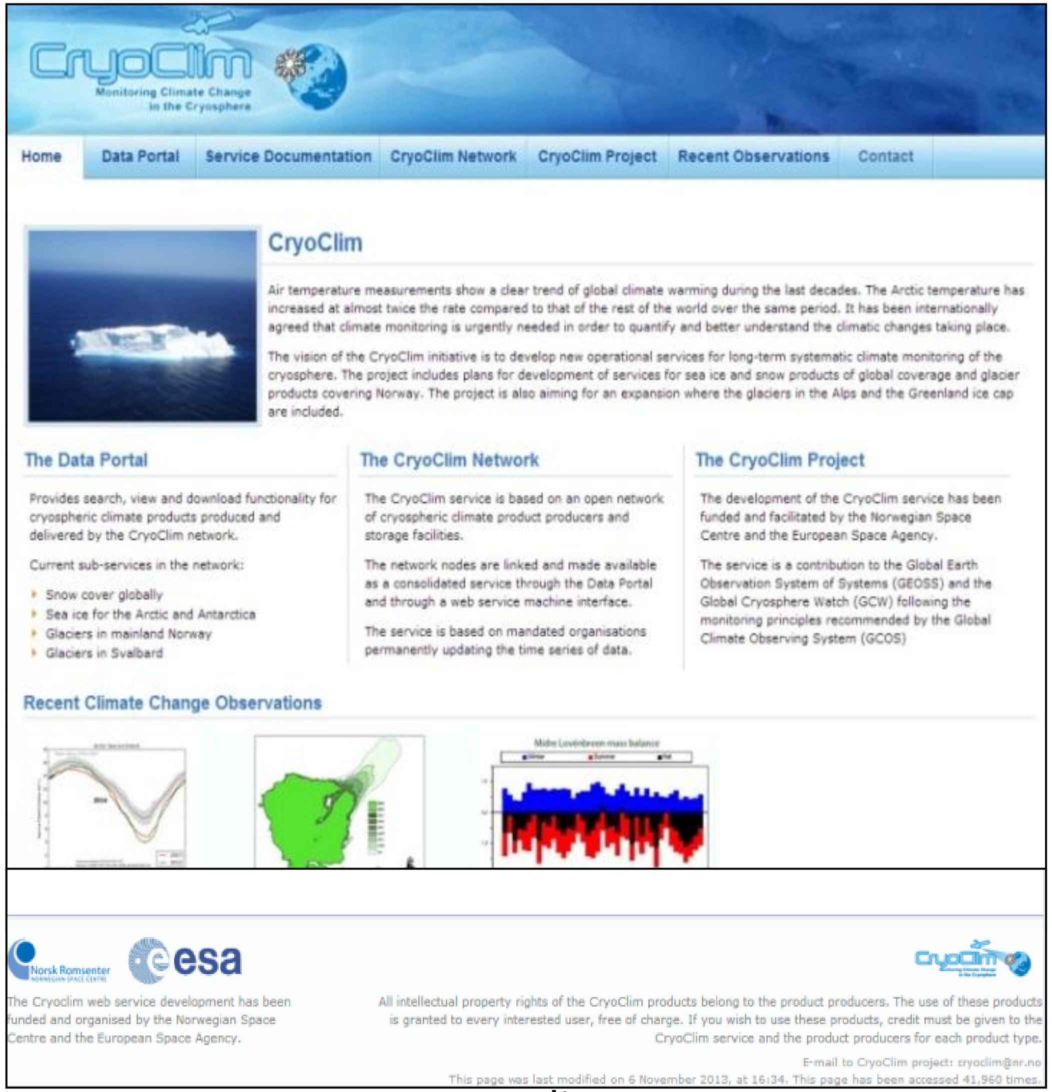
10th EARSeL Workshop on Land Ice and Snow,
Bern, Switzerland,
6 - 8 February 2023

EARSeL

1) Norwegian Computing Center, Section for Earth Observation, Oslo, Norway
2) Norwegian Meteorological Institute, Oslo, Norway
3) Eurac Research, Bolzano, Italy

Summary of past CryoClim work

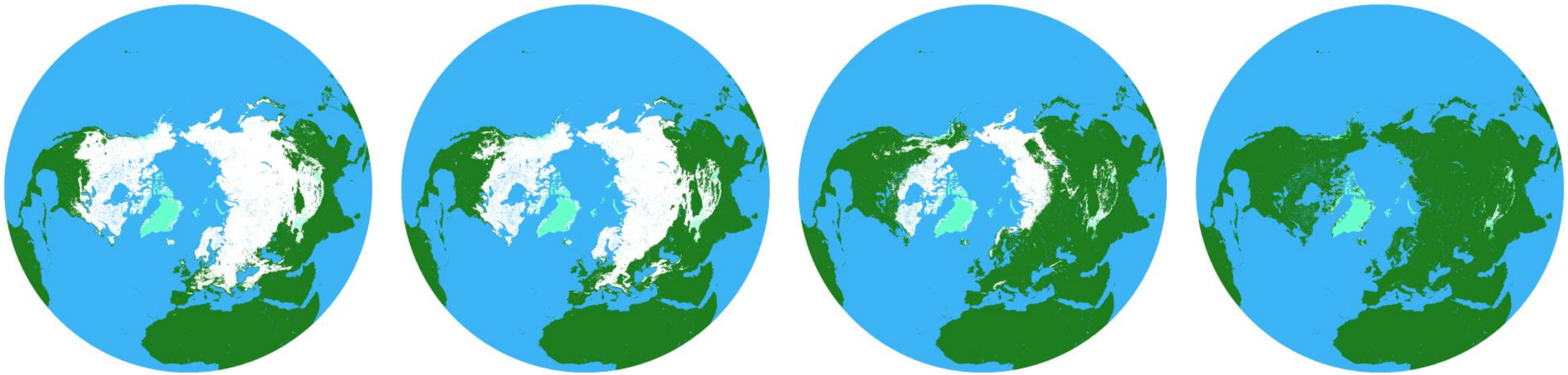
- Long-term time series of daily, global snow observations of full spatio-temporal coverage independent of clouds and polar night (1982-present)
- Based on a fusion algorithm combining observation from optical and passive microwave radiometers (PMR) - AVHRR GAC and SMMR+SSM/I+SSMIS data
- SCE Version 1 (2013): The CryoClim project (2008-2013) developed first version of algorithms, products and a service for cryospheric climate monitoring: www.cryoclim.net
- SCE Version 1.5 (2017): Mitigated weaknesses in original algorithm, included uncertainty estimation, tested use of Sentinel-3 SLSTR and extended the time series until 2015
- FSC Version 2.0 (2022): Fractional snow cover (FSC). Developed under ESA Snow CCI.



www.cryoclim.net

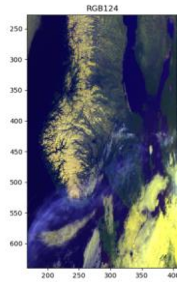
Snow_CCI: From SCE (binary) to FSC

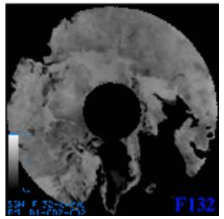
- The main objective was to further develop the CryoClim snow algorithm to obtain fractional snow cover (FSC), i.e. snow cover on a continuous scale from 0% to 100%
- This is motivated by the aim of providing FSC according to ESA's requirements for snow extent monitoring in Snow CCI [TR-5] – which is again based on GCOS requirements – and that future algorithm development would most likely aim at combining optical data with complementary EO data to achieve better coverage in space and time (in line with [TR-9]), as we already have demonstrated with the current CryoClim snow product



CryoClim multi-sensor multi-temporal model

Optical





PMR

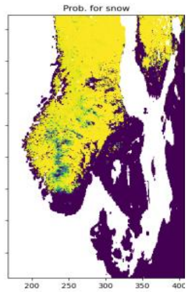
Bayesian model combining different features

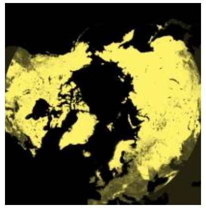
$$P(S_k|\mathbf{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_n) = \frac{p(\boldsymbol{x}_1|S_k)\cdot p(\boldsymbol{x}_2|S_k)\cdots p(\boldsymbol{x}_n|S_k)\cdot P(S_k)}{\sum_{m=1}^{M} p(\boldsymbol{x}_1|S_m)\cdot p(\boldsymbol{x}_2|S_m)\cdots p(\boldsymbol{x}_n|S_m)\cdot P(S_m)}$$

Bayesian model combining different features

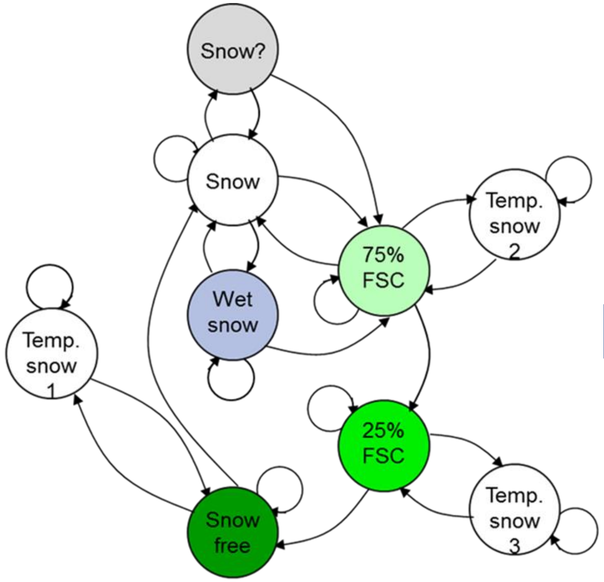
$$P(S_k|\mathbf{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_n) = \frac{p(\boldsymbol{x}_1|S_k)\cdot p(\boldsymbol{x}_2|S_k)\cdots p(\boldsymbol{x}_n|S_k)\cdot P(S_k)}{\sum_{m=1}^{M} p(\boldsymbol{x}_1|S_m)\cdot p(\boldsymbol{x}_2|S_m)\cdots p(\boldsymbol{x}_n|S_m)\cdot P(S_m)}$$

Single sensor algorithms

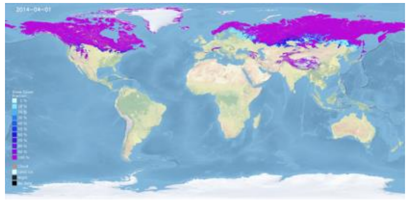




Probabilities



Fusion model

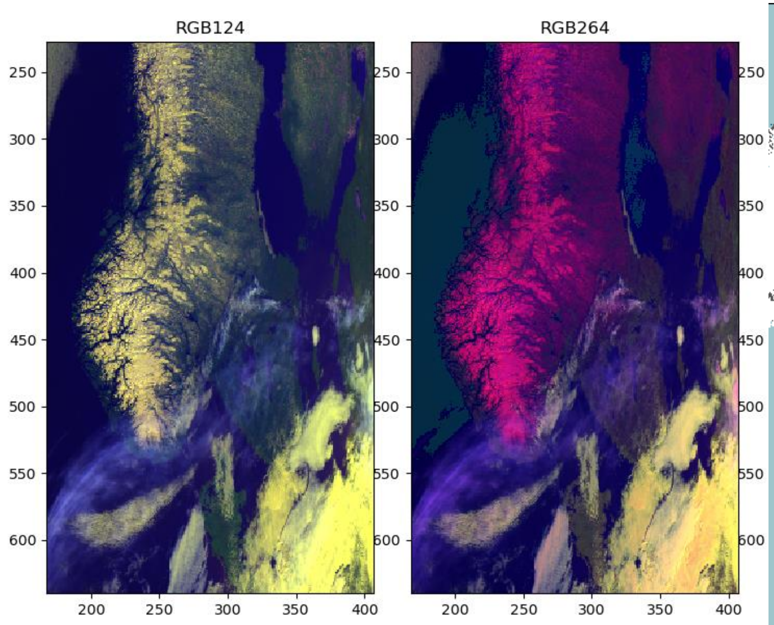


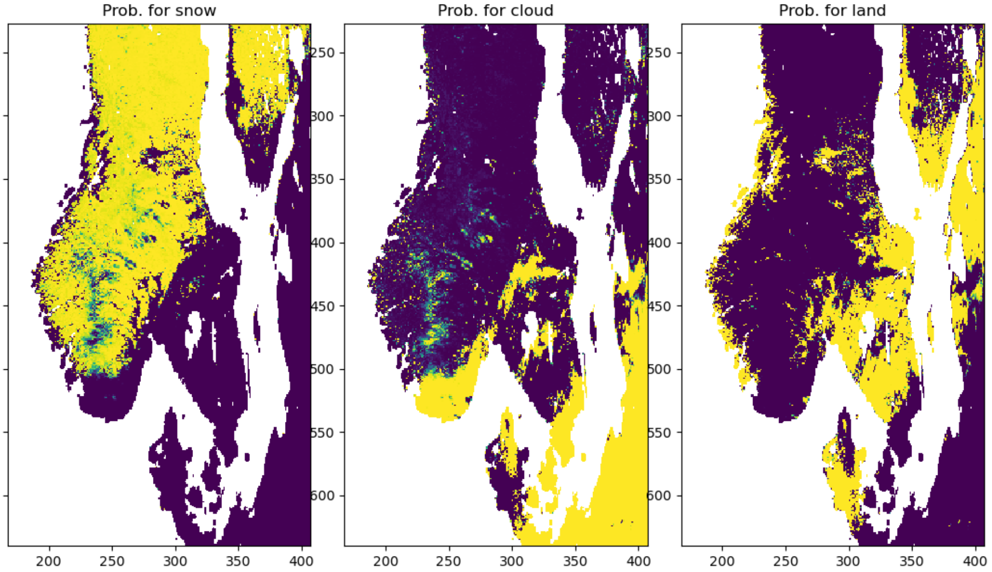
FSC map

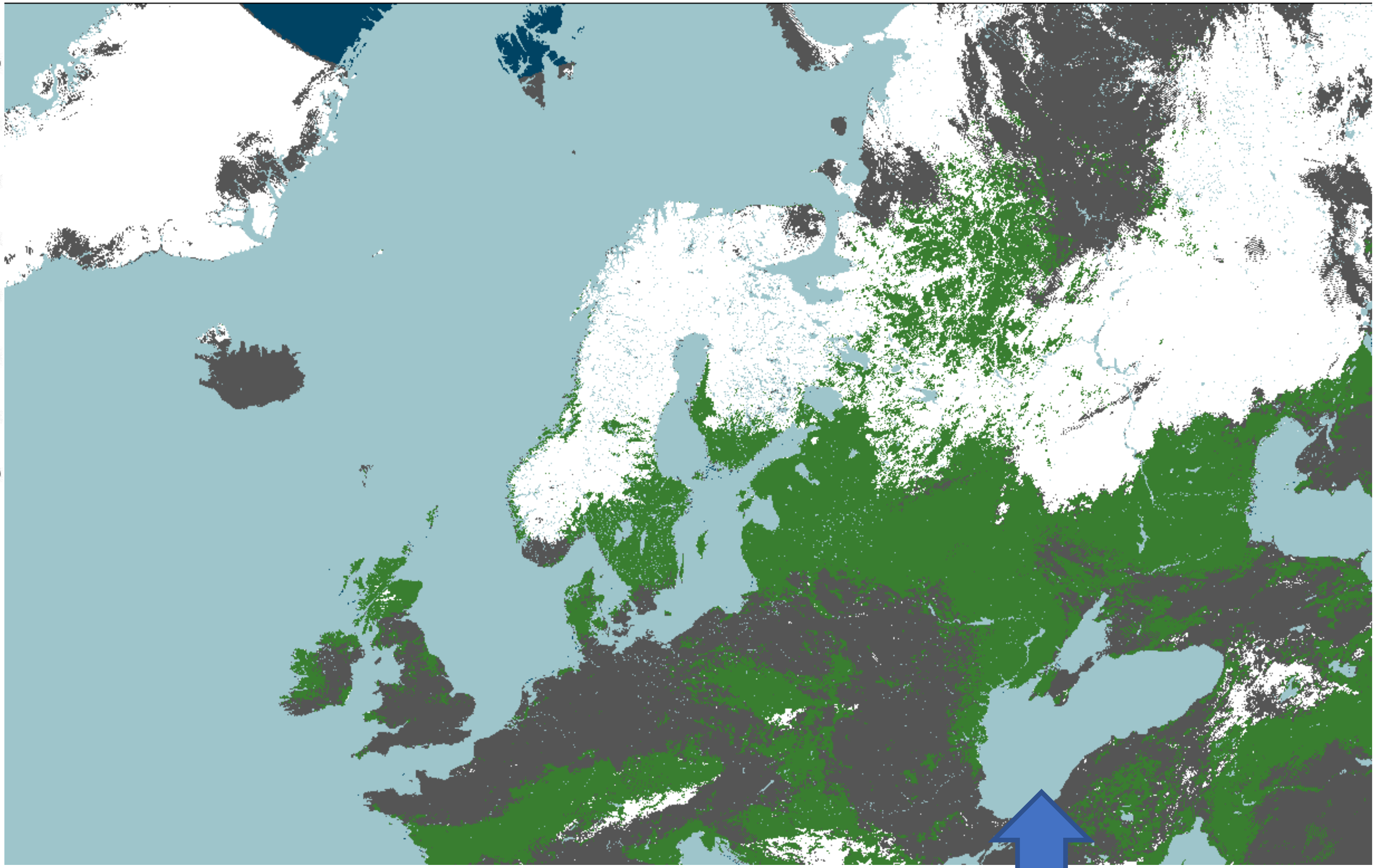
The optical component

AVHRR GAC passage product

MetOp-A
15 March 2015
10:07 UTC







Bayesian model combining different features

$$P(S_k|\mathbf{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_n) = \frac{p(\boldsymbol{x}_1|S_k) \cdot p(\boldsymbol{x}_2|S_k) \cdots p(\boldsymbol{x}_n|S_k) \cdot P(S_k)}{\sum_{m=1}^{M} p(\boldsymbol{x}_1|S_m) \cdot p(\boldsymbol{x}_2|S_m) \cdots p(\boldsymbol{x}_n|S_m) \cdot P(S_m)}$$

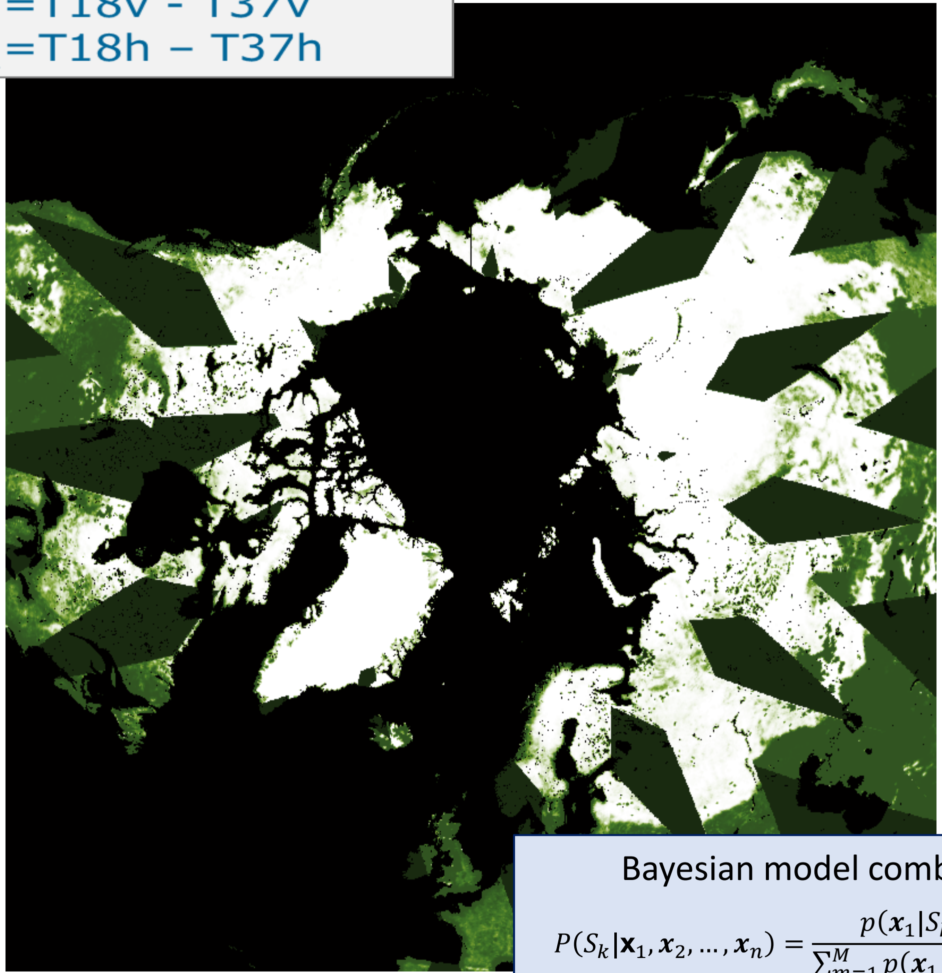
The PMR component

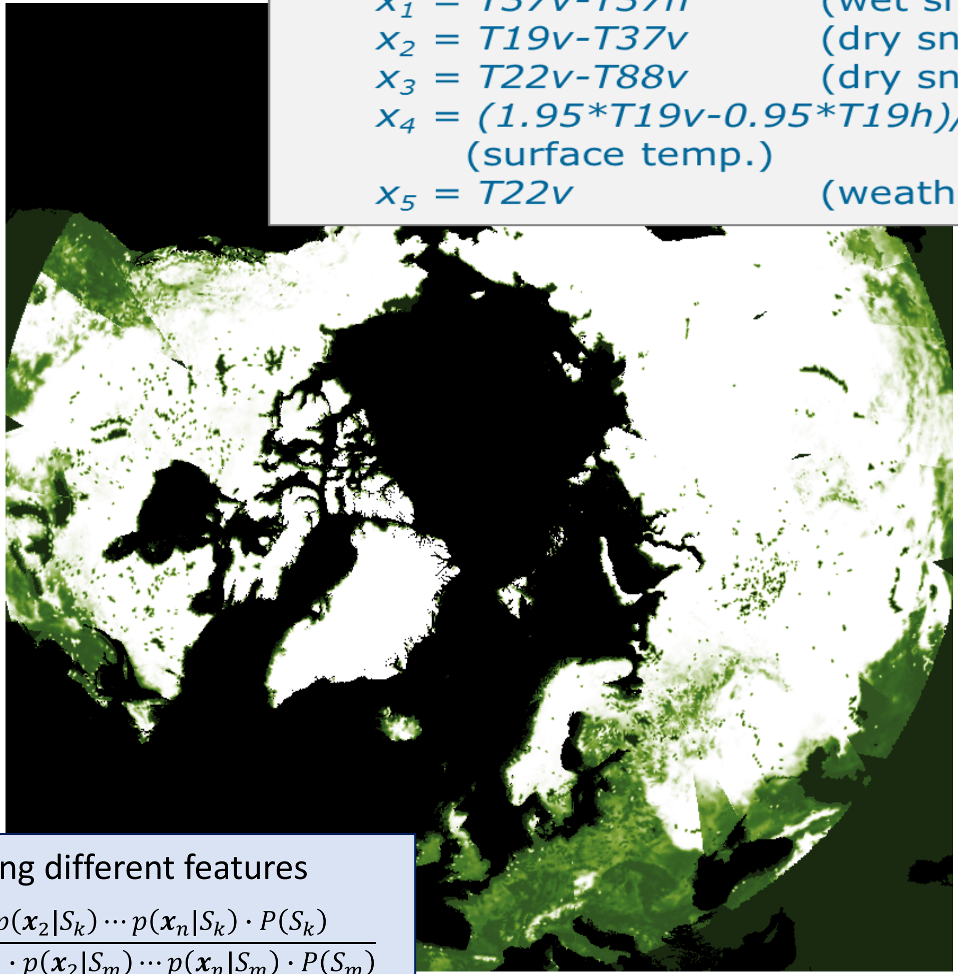
SMMR features:

x_1=T18v - T37v
x_2=T18h – T37h

SSM/I features:

x_1 = T37v-T37h (wet snow)
x_2 = T19v-T37v (dry snow)
x_3 = T22v-T88v (dry snow)
x_4 = (1.95*T19v-0.95*T19h)/0.95 (surface temp.)
x_5 = T22v (weather)





Bayesian model combining different features

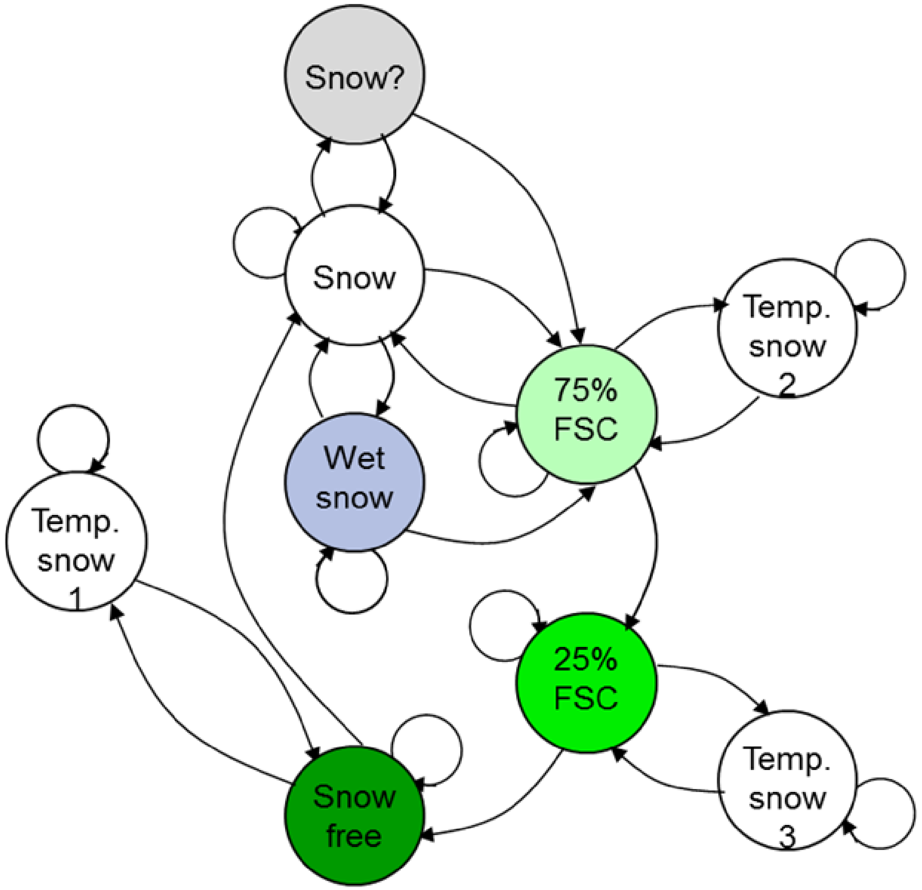
$$P(S_k|\mathbf{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_n) = \frac{p(\boldsymbol{x}_1|S_k)\cdot p(\boldsymbol{x}_2|S_k)\cdots p(\boldsymbol{x}_n|S_k)\cdot P(S_k)}{\sum_{m=1}^{M} p(\boldsymbol{x}_1|S_m)\cdot p(\boldsymbol{x}_2|S_m)\cdots p(\boldsymbol{x}_n|S_m)\cdot P(S_m)}$$

Snow Cover Extent from 12 March 1983 based on SMMR

Snow Cover Extent from 1 March 2010 based on SSM/I

HMM simulating snow development

- The fusion algorithm is based on a hidden Markov model (HMM) simulating the snow states based on the satellite observations
- The basic idea is to simulate the states the snow surface goes through during the snow season with a state model
- The model is described by the different states and the possible transitions between these states. The states are given by probability density functions and the transitions by transition probabilities
- The transition probabilities depend on the current time within the season. The states are not directly observable, but the remote sensing observations give data describing the snow conditions, which are related to the snow states
- A Viterbi algorithm is used to find the most likely snow cover sequence throughout the hydrological year at a given location. The HMM solution represents not only a multi-sensor model but also a multi-temporal model



The fusion algorithm

- The fusion algorithm is based on a hidden Markov model (HMM) simulating the snow states based on the satellite observations
- The basic idea is to simulate the states the snow surface goes through during the snow season with a state model
- The model is described by the different states and the possible transitions between these states. The states are given by probability density functions and the transitions by transition probabilities
- The transition probabilities depend on the current time within the season. The states are not directly observable, but the remote sensing observations give data describing the snow conditions, which are related to the snow states
- A Viterbi algorithm is used to find the most likely snow cover sequence throughout the hydrological year at a given location. The HMM solution represents not only a multi-sensor model but also a multi-temporal model

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

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

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

Transition probabilities.:

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

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

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

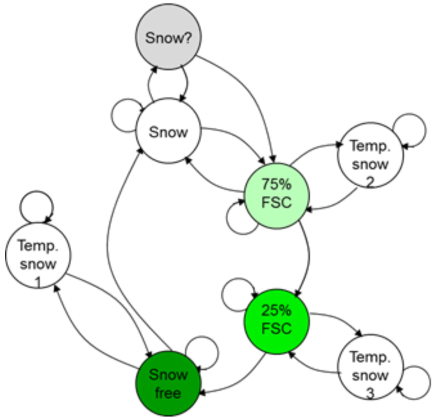
$$V_{t,k} = p(X^t | k) \max_i \left(p\left(E^t = S_i \middle| E^{t-1} = S_j\right) V_{t-1,k}\right)$$

Sensor fusion combining single-sensor state models

Weaknesses:
- Depends on clear weather
- No coverage during polar night

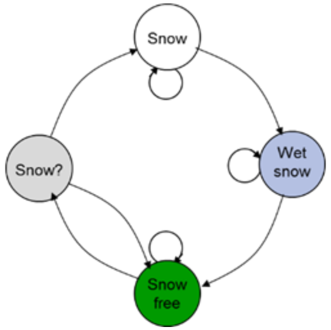
Strengths:
- Accurate
- High resolution

Optical

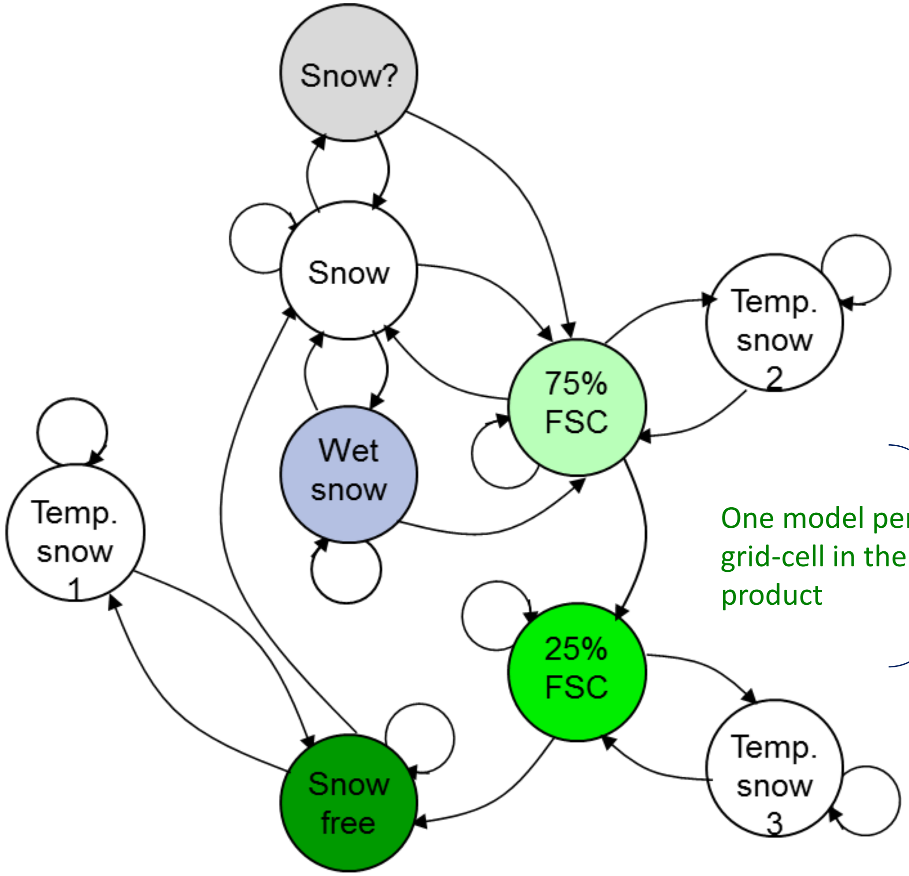


Weaknesses:
- Insensitive to small snow depths
- Not robust for detection of wet snow
- Low spatial resolution

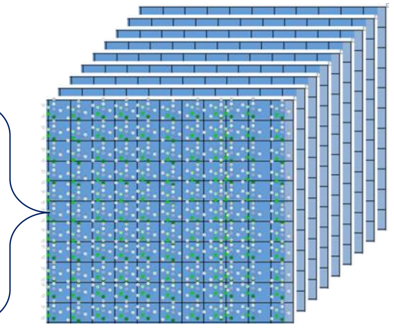
Strengths:
- Less sensitive to clouds
- Coverage during polar night



Passive microwave radiometer



One model per grid-cell in the product

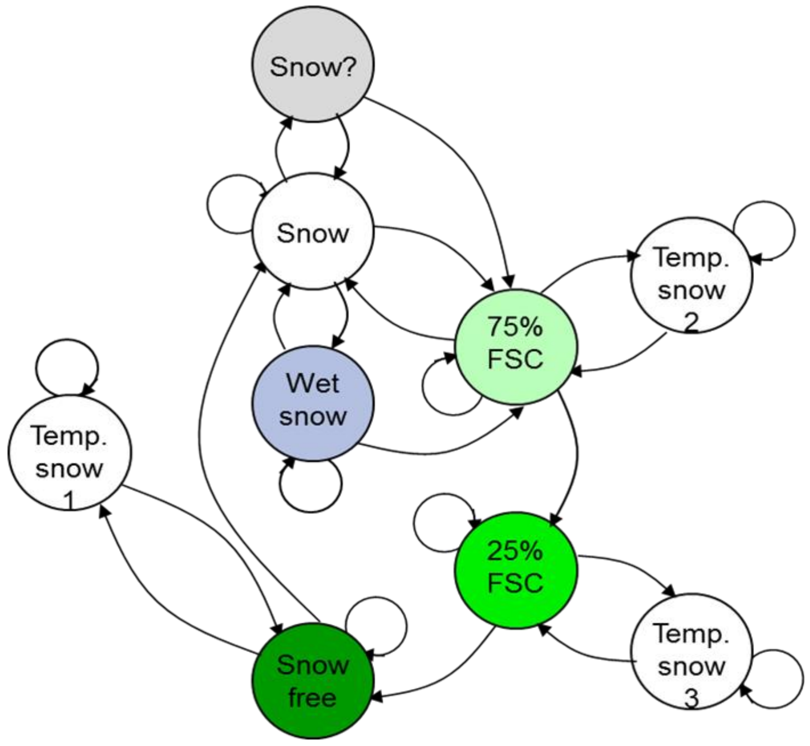


Multi-sensor multi-temporal

Utilising the complementarity of the sensors

From a binary product to 1% resolution

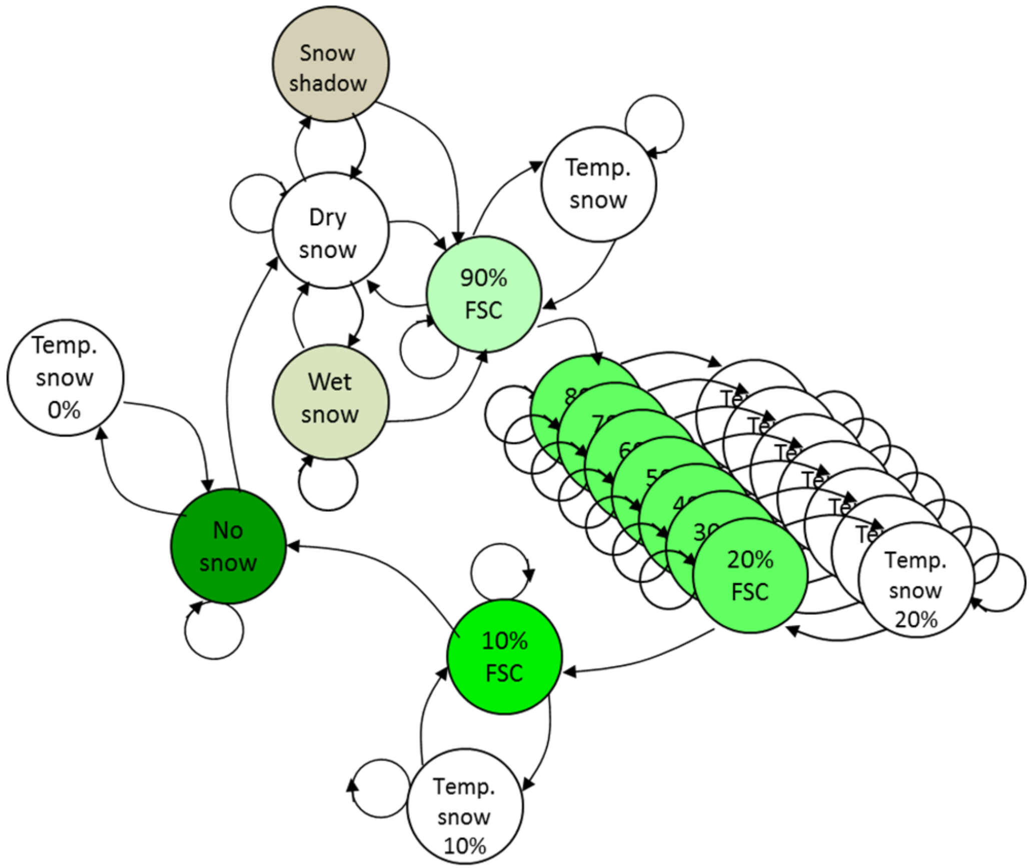
- CryoClim SCE product (binary):
  - Binary: snow/no snow
  - HMM using 9 snow states
  - Each state is classified as snow/no snow
- Snow_CCI CryoClim FSC products
  - Fractional snow cover: 1% resolution
- Simply expanding the HMM to allow a fractional snow cover requires 203 snow states
  - Computationally prohibitive
  - Changes the dynamic of the algorithm
  - **Many** more possible transitions to tune
  - This is difficult to compensate for



CryoClim SCE (binary)

From a binary product to 1% resolution

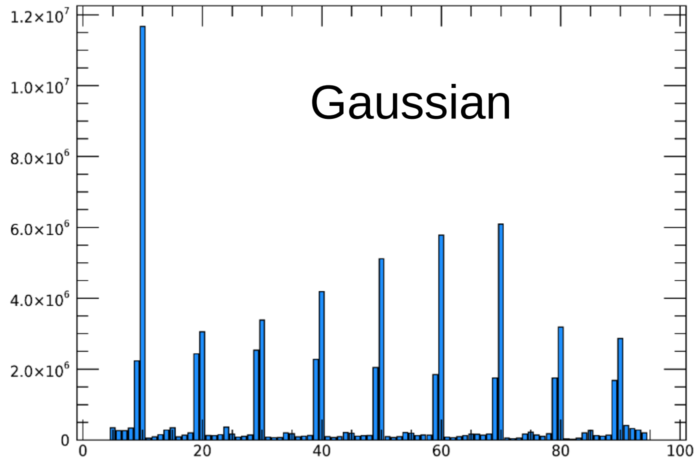
- We use a HMM with 10% snow fraction resolution
  - 23 snow states
- The sequence of snow states are found using the Viterbi algorithm as before
  - Hereafter referred to as primary states
- In addition, we also find a secondary state for each time step
  - The second most probable state
- The snow fraction is found by a weighted average of the primary and secondary states, using the cumulative probability of the states as weights

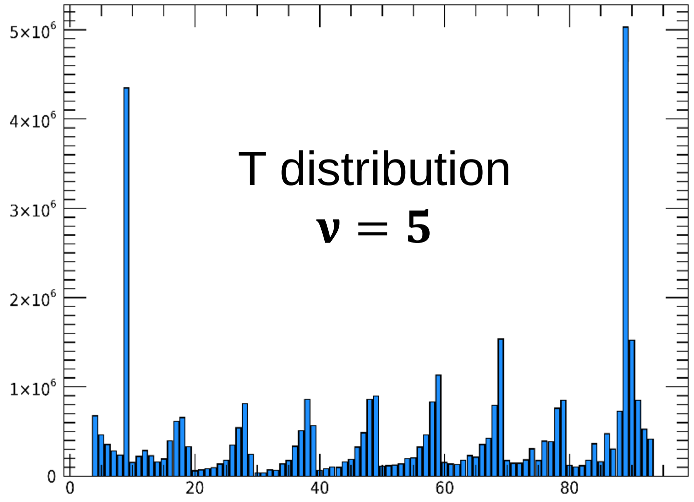


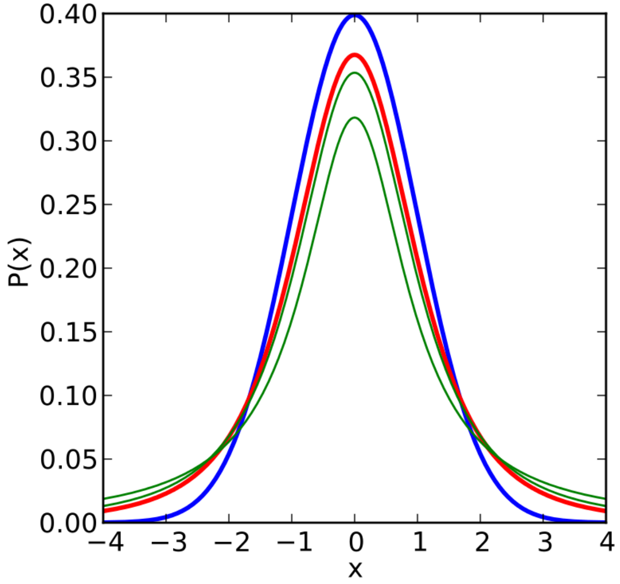
Snow_CCI CryoClim FSC

From a binary product to 1% resolution

- Using Gaussian distribution, the algorithm *strongly* favours the most probable state
- This gives a much stronger weight for the primary state, so it dictates the final FSC
- Apparently, this is typical for Gaussian models
- Mitigated by using Student’s t-distribution instead



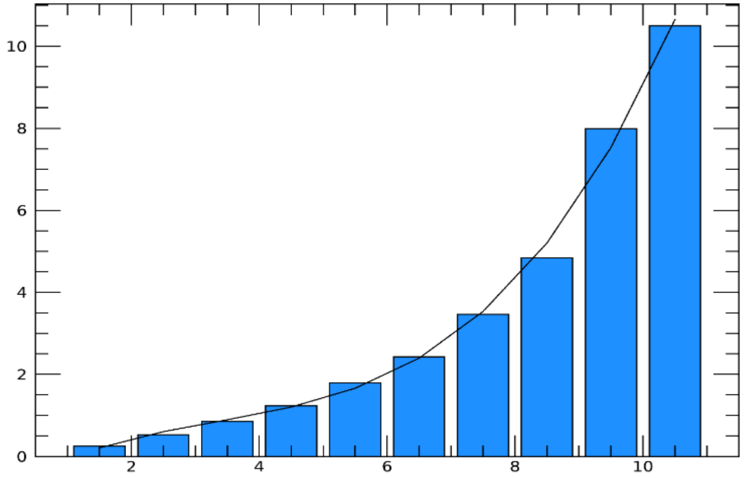




Gaussian distribution (blue), Student’s t distribution with 3 degrees of freedom (red) and 1 and 2 degrees of freedom (green). *Wikimedia Commons*

Histogram equalisation

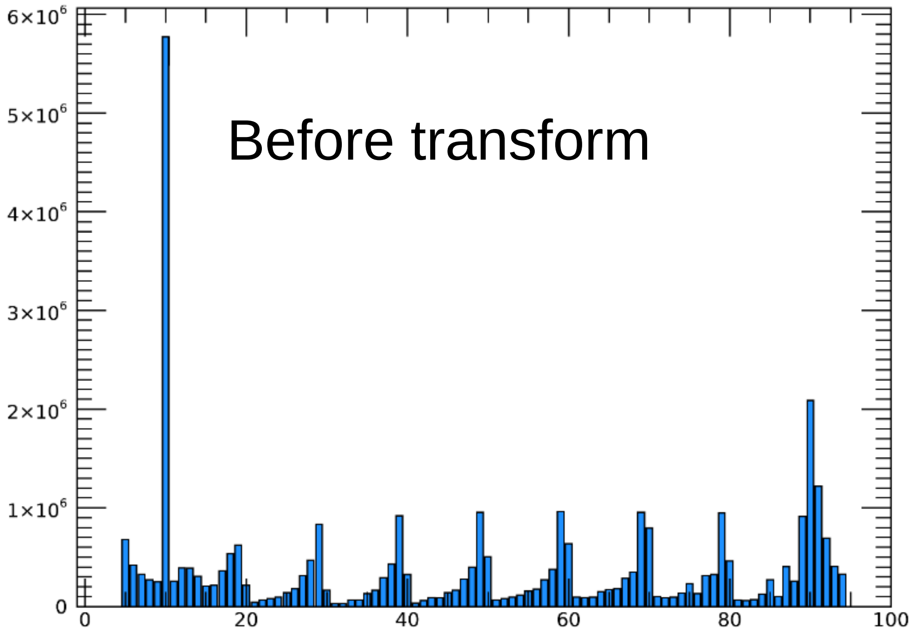
- Create a histogram transform to equalize the artificial peaks
- Applied histogram from three years:
  - 1990-1991, 2000-2001, 2010-2011
- Added the peaks from the interval $21 \leq FSC \leq 80$
- Found the cumulative histogram, and fitted with a polynomial
- This polynomial was then used as a transform to equalize the FSC histogram within each 10% FSC interval
  - Only transform partial snow cover, $1 \leq FSC \leq 99$

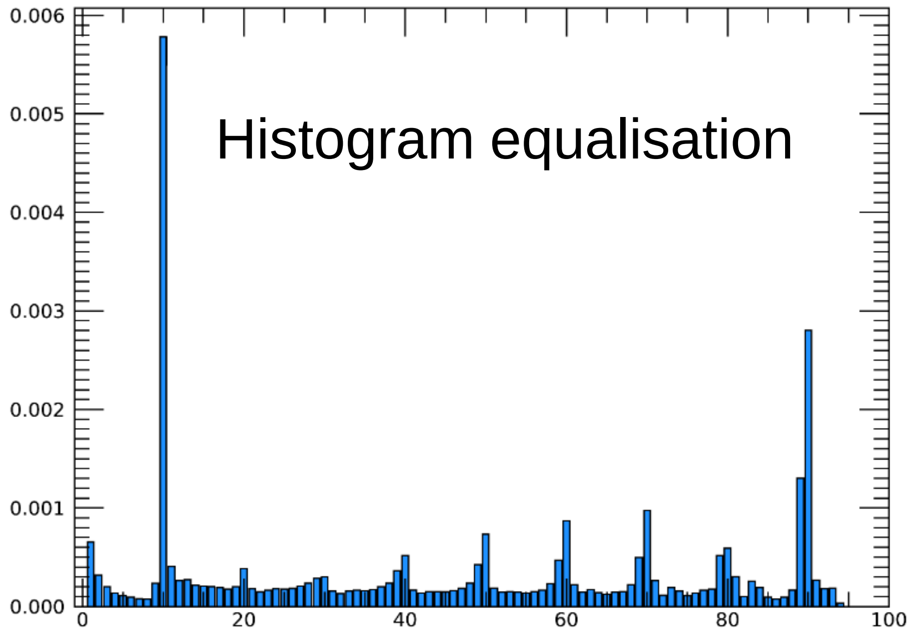


Histogram transform:

1. $x = (FSC-1) \bmod 10 + 1.5$
2. $y = c_3x^3 + c_2x^2 + c_1x + c_0$
3. $FSC_{new} = y + FSC - x$

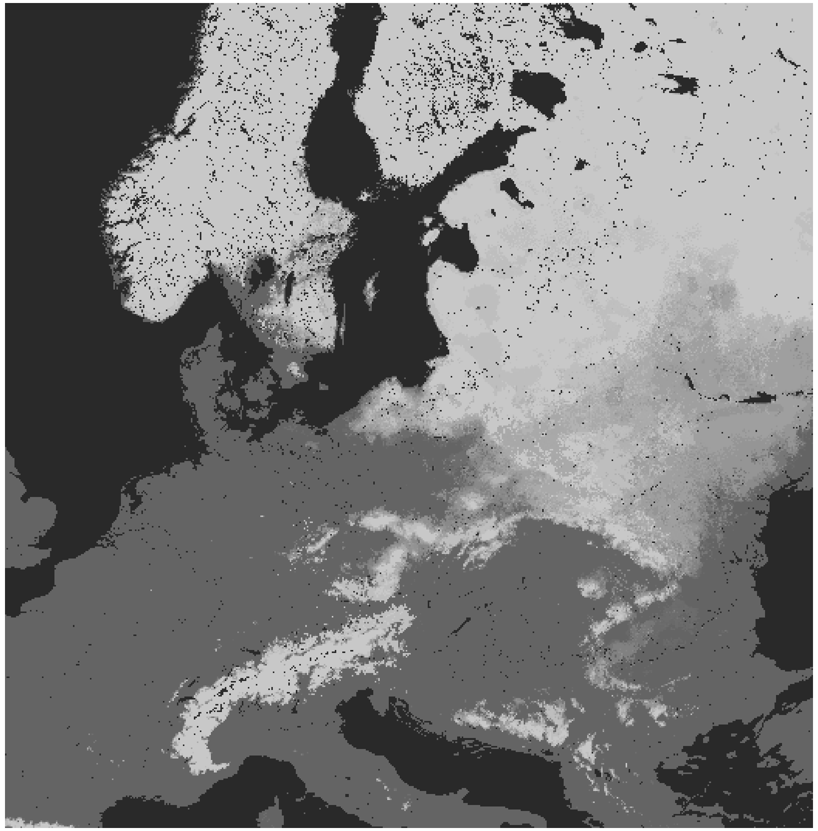
Example: Histogram equalisation 2003-2004



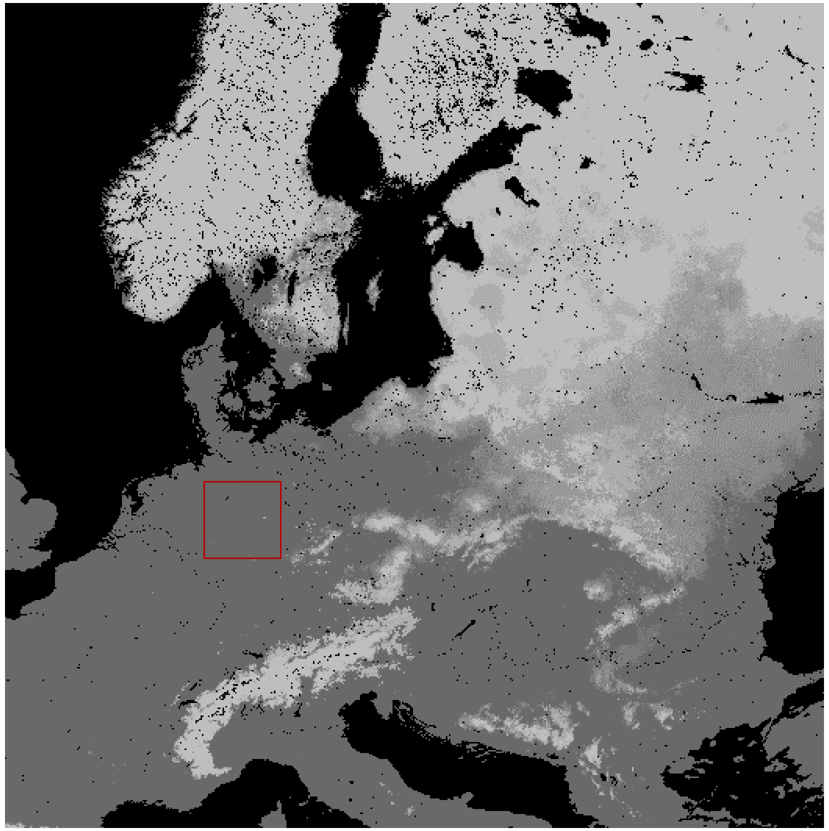


Dataset	Entropy 11-89	Entropy 21-79
FSC, Gauss, 1995	3.26	2.92
FSC, t-distribution, $\nu = 5$, 1995	4.05	3.71
1995, equalized	4.12	3.82
2003, equalized	4.15	3.89

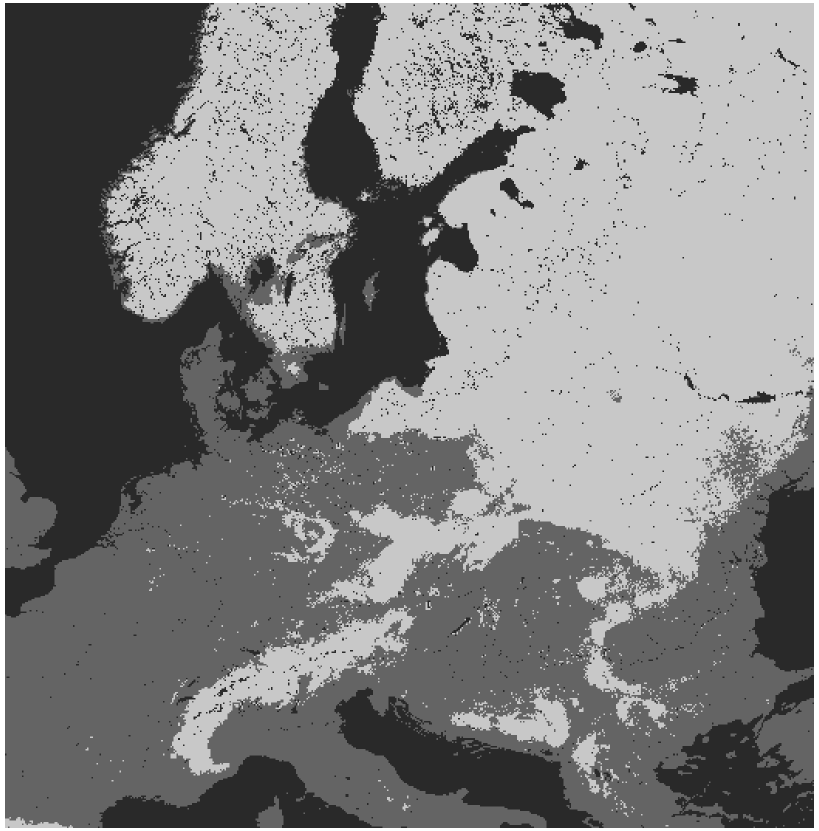
Example data: 1 April 1996



FSC: T-distribution, $\nu = 5$



Histogram equalisation



Binary

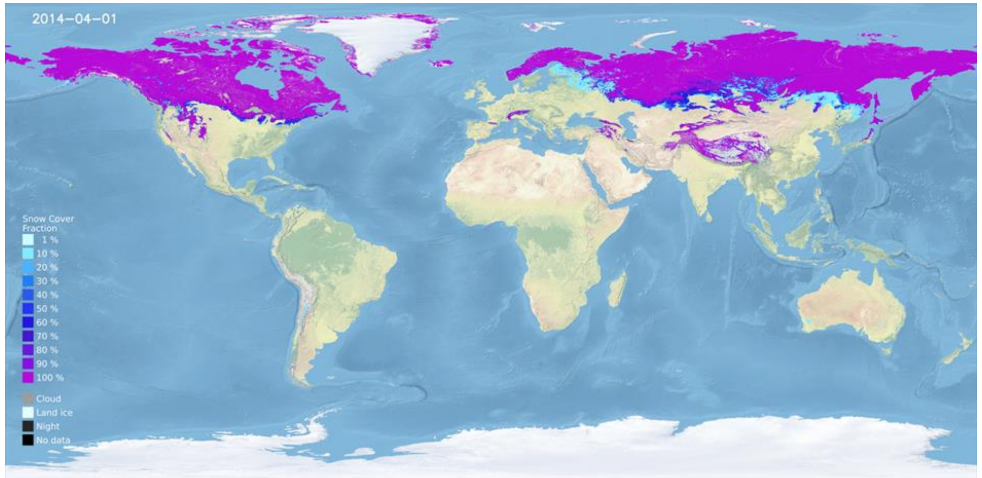
Uncertainty estimation

snow cci

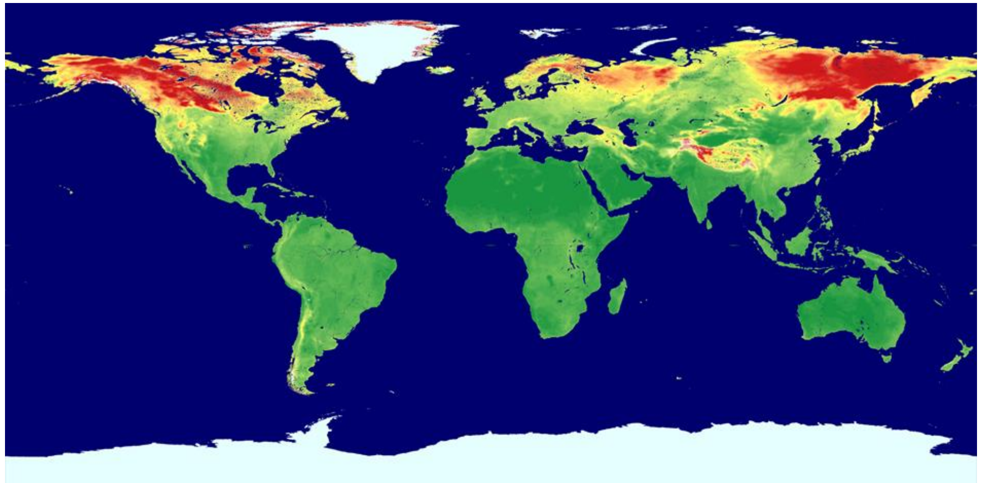
- The RMSE was estimated using a logistic regression model approach
- Based on the uncertainty models from the *snow_cci* AVHRR product and the previous CryoClim 2.0 SCE product
- The pixel-wise RMSE is estimated as:

$$RMSE = \frac{exp(\eta)}{1 + exp(\eta)}.$$

- $\eta = 15.05 - 0.051 \cdot ll_s + 0.019 \cdot |d| - 0.061 \cdot T$
    - T is the surface temperature estimated by the PMR data
    - $|d|$ is the time interval to nearest cloud-free optical observation
    - ll_s is the data log-likelihood of the no-snow states.



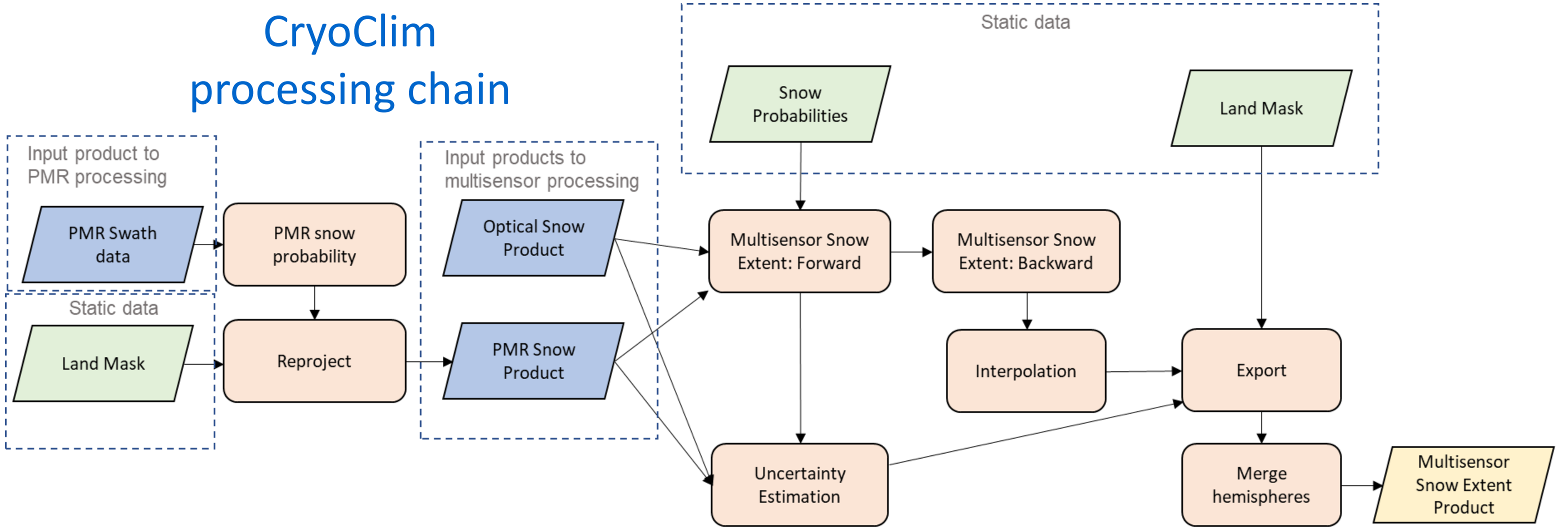
Snow_cci CryoClim FSC product example for 1 April 2014



Snow_cci CryoClim FSC uncertainty example for 1 April 2014

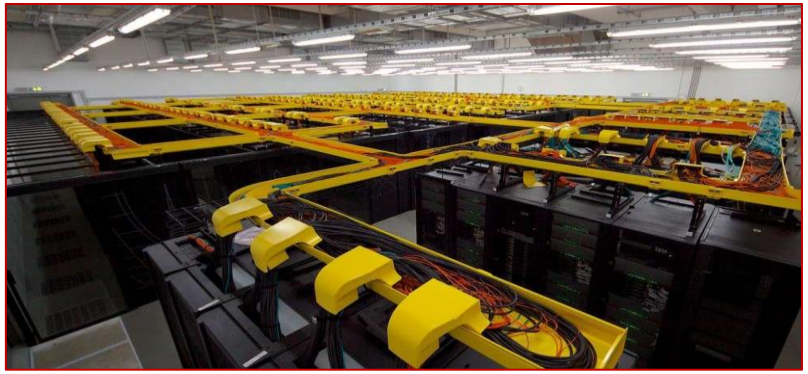
Use of Fram supercomputer

CryoClim processing chain



NR, Oslo

Scalable Peta Byte storage system at NR
Current contents: Terra MODIS Col. 6.1
1999-present, 220 TB

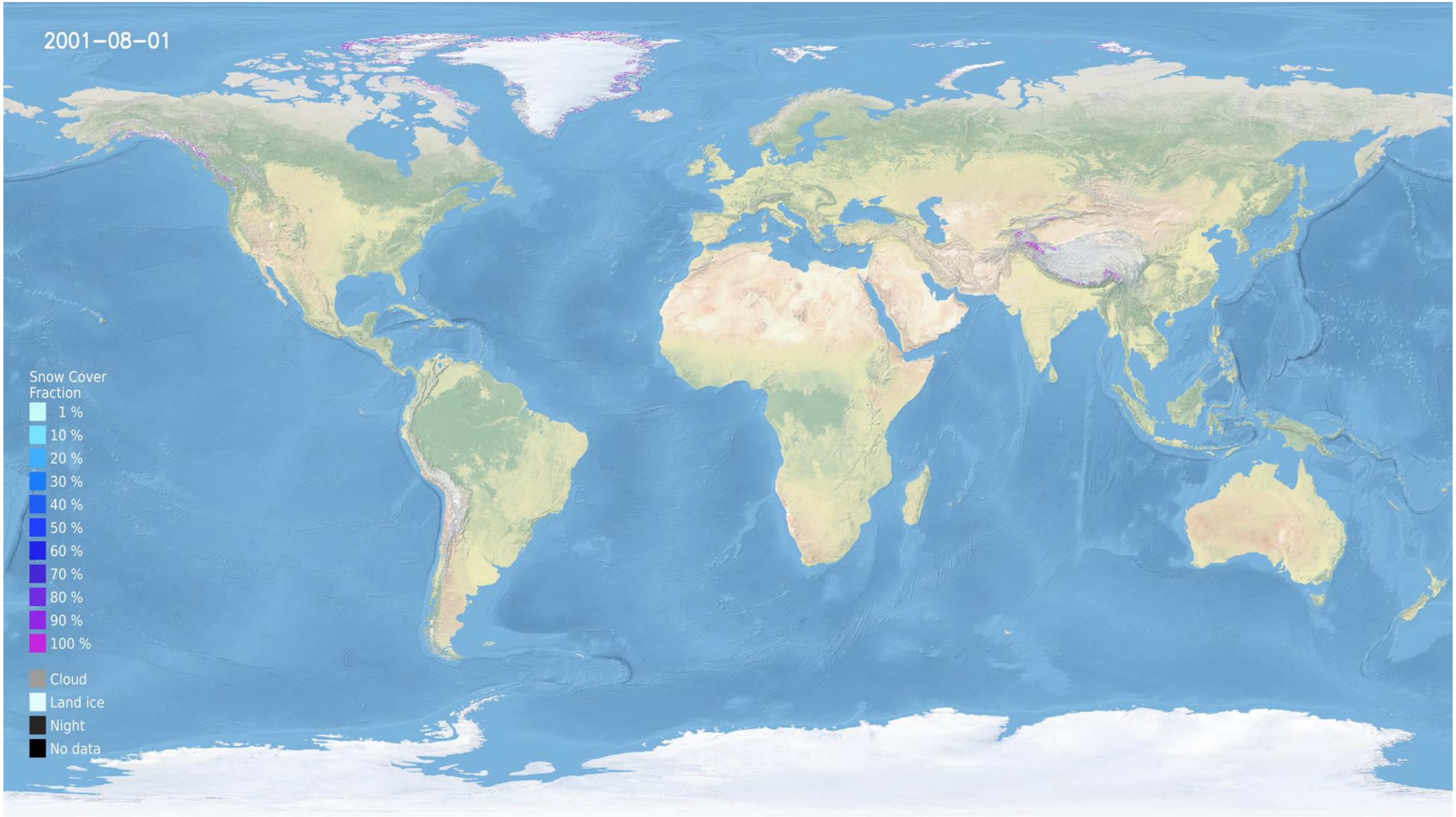


Fram national HPC:

- **32,256 cores**
- **1006 nodes**
- **1.1 petaflops**
- **78 TB RAM**
- **2.5 PB local storage**

Fram, Tromsø

Timelapse video of snow maps 2001/2



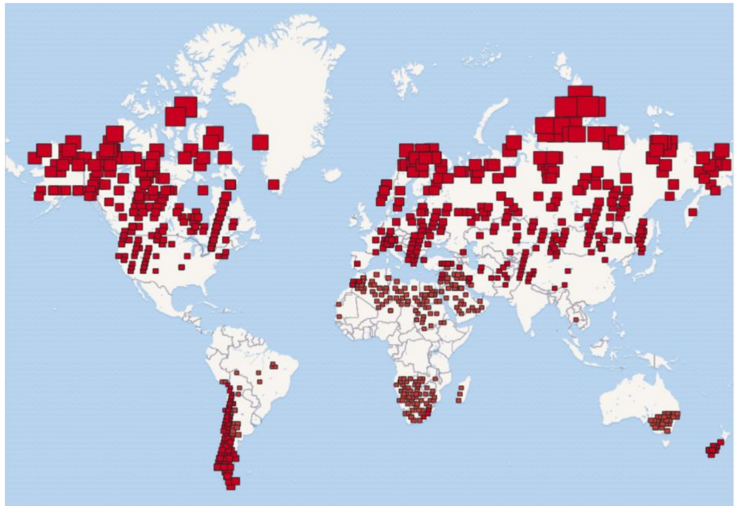
Product Validation

- Study the performance of the new CryoClim FSC product relative to the previous CryoClim SCE binary product using the same validation approach and in situ data as in the previous CryoClim project activities

- Study the performance of the new CryoClim FSC product with respect to the Snow_CCI baseline project's high-resolution based reference data (393 scenes)

Data set	Spatial coverage	Stations	Temporal coverage	Temporal frequency	Variables	Note
Global Historical Climatology Network – Daily (GHCN-D)	Global	> 100,000	1890 - present	Daily	Snow depth	180 countries contribute, but stations are unevenly distributed
Snow Cover Characteristics from Russian Meteorological Stations and Former USSR (RIHMI)	Russia and former Soviet Union	Up to 600	1958- present	Daily. Snow course surveys from monthly to every 5 days.	Snow depth, snow cover (scale of 0 to 10), snow characteristics. Snow course surveys: snow depth, snow density, SWE, snow characteristics.	Incomplete documentation of field values. Some conflicting data.
Historical Soviet Daily Snow Dataset (HSDSD)	Russia and former Soviet Union	Up to 280	01.01.1881 - 31.12.1995	Daily	Snow depth, snow cover (scale of 0 to 10)	Incomplete documentation of field values. Inaccurate location data.
Former Soviet Union Hydrological Snow Surveys (FSUHSS)	Former Soviet Union	Up to 1345 (ca. 200 after 1991)	10.01.1966- 31.12.1996	3 times per month	Transects of snow coverage (scale of 0 to 10), snow density, snow depth, SWE, snow characteristics.	Only measurements in the winter. Lacking reliable observations of no snow. Inaccurate location data.

Point measurements from stations and snow courses



High-resolution Landsat scenes used to make validation snow maps

Binary FSC validation vs. in situ stations

Year	GHCN-D accuracy (%)		RIHMI accuracy (%)		HSDSD accuracy (%)		FSUHSS accuracy (%)	
	snow_cci CryoClim FSC	CryoClim SCE v. 2.0	snow_cci CryoClim FSC	CryoClim SCE v. 2.0	snow_cci CryoClim FSC	CryoClim SCE v. 2.0	snow_cci CryoClim FSC	CryoClim SCE v 2.0
1982	91	90	90	89	92	92	--	--
1983	89	90	88	89	90	91	--	--
1984	89	89	82	84	91	90	--	--
1985	85	90	85	90	91	92	--	--
1986	88	90	87	91	92	92	--	--
1987	89	89	92	91	94	91	--	--
1988	92	85	92	89	94	86	--	--
1989	92	86	92	90	94	85	--	--
1990	92	86	92	89	94	85	--	--
1991	92	87	93	90	94	86	95	97
1992	93	90	92	92	94	92	94	96
1993	93	91	92	93	94	93	93	96
1994	93	92	92	93	94	94	93	96
1995	93	92	92	93	95	94	94	96
1996	93	91	92	93	--	--	94	96
1997	93	92	92	93	--	--	--	--
1998	93	92	92	93	--	--	--	--
1999	93	91	92	93	--	--	--	--

Binary FSC validation vs. in situ stations

Year	GHCN-D accuracy (%)		RIHMI accuracy (%)		HSDSD accuracy (%)		FSUHSS accuracy (%)	
	snow_cci CryoClim FSC	CryoClim SCE v. 2.0	snow_cci CryoClim FSC	CryoClim SCE v. 2.0	snow_cci CryoClim FSC	CryoClim SCE v. 2.0	snow_cci CryoClim FSC	CryoClim SCE v. 2.0
2000	93	91	91	92	--	--	--	--
2001	94	93	93	94	--	--	--	--
2002	93	92	92	93	--	--	--	--
2003	94	93	93	94	--	--	--	--
2004	95	93	93	94	--	--	--	--
2005	94	93	93	94	--	--	--	--
2006	94	93	92	93	--	--	--	--
2007	94	93	93	93	--	--	--	--
2008	93	91	94	94	--	--	--	--
2009	92	91	95	95	--	--	--	--
2010	93	91	95	95	--	--	--	--
2011	93	92	95	94	--	--	--	--
2012	93	90	95	94	--	--	--	--
2013	93	92	95	94	--	--	--	--
2014	94	93	94	94	--	--	--	--
2015	94	93	94	94	--	--	--	--

Seasonal accuracy for year 2014

Month	GHCN-D accuracy (%)		RIHMI accuracy (%)	
	snow_cci CryoClim FSC	CryoClim SCE v. 2.0	snow_cci CryoClim FSC	CryoClim SCE v. 2.0
January	89	88	94	95
February	90	90	95	97
March	91	91	92	94
April	91	90	91	90
May	96	94	95	94
June	99	99	99	98
July	100	100	100	99
August	100	100	100	99
September	100	99	98	96
October	98	97	86	85
November	89	87	87	86
December	88	86	90	91

Overall accuracy based in *snow_cci* HR data

Summary of the SCFG validation of the *snow_cci* CryoClim FSC products.

	Salomonson	*Klein*	*Dozier*
RMSE	15.5	15.80	16.41
Unbiased RMSE	15.32	15.80	16.31
Bias	2.38	-0.07	1.87
Correlation Coefficient	0.94	0.93	0.92

Summary of the SCFG validation of the *snow_cci* CryoClim FSC products separating forest from open areas.

	Salomonson forested	*Salomonson open areas*	*Dozier open areas*	*Klein open areas*
RMSE	17.93	13.47	13.89	13.91
Unbiased RMSE	17.52	13.40	13.83	13.85
Bias	3.79	1.35	1.32	1.29
Correlation Coefficient	0.93	0.9	0.9	0.9

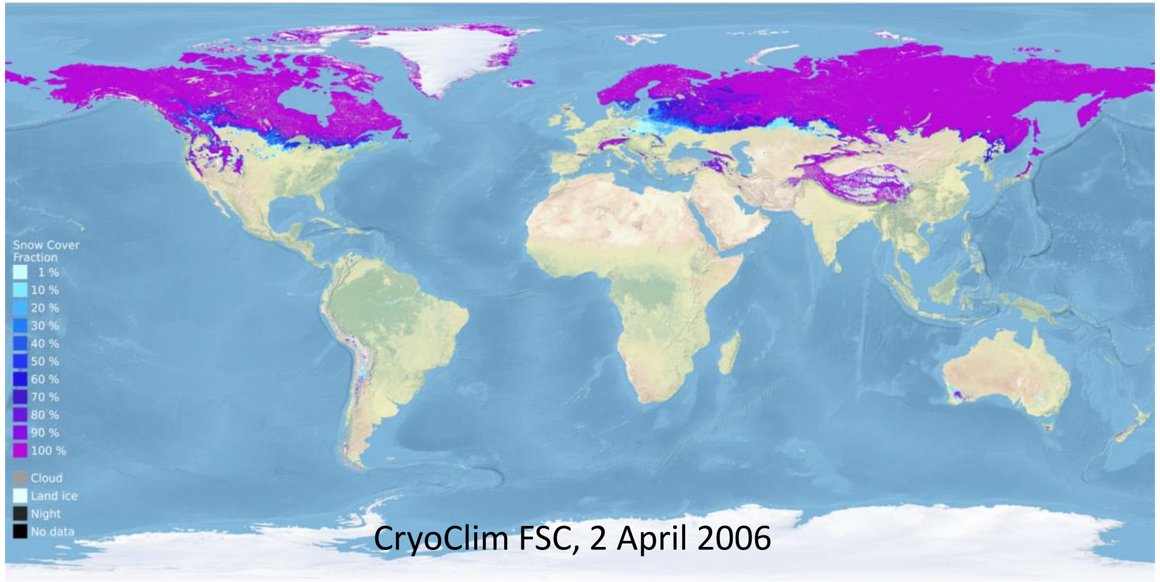
Overall accuracy based in *snow_cci* HR data

Summary of the SCFG validation of the *snow_cci* CryoClim FSC uncertainty estimates (non-forested areas only).

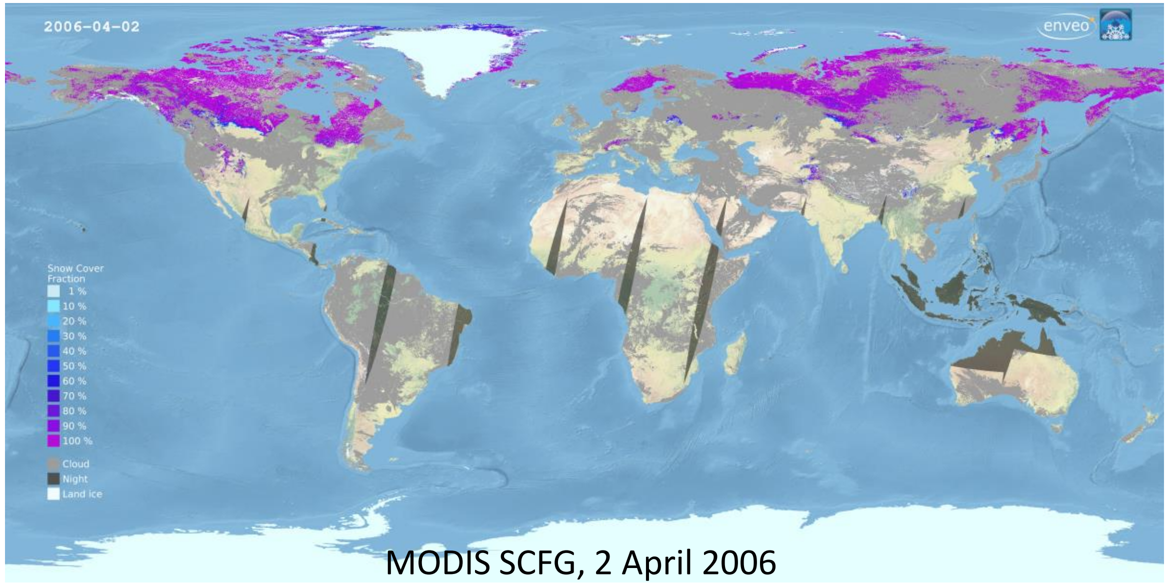
	Salomonson	***Klein***	***Dozier***
RMSE	13.40	15.94	15.51
Bias	1.89	2.99	2.50

A general overestimation of the uncertainty provided by *snow_cci* CryoClim FSC uncertainty estimates of an order of 2 to 3% depending on the method used for the intercomparison. The RMSE is relatively high (around 15%) indicating a large variance of the error in the provided uncertainty layer.

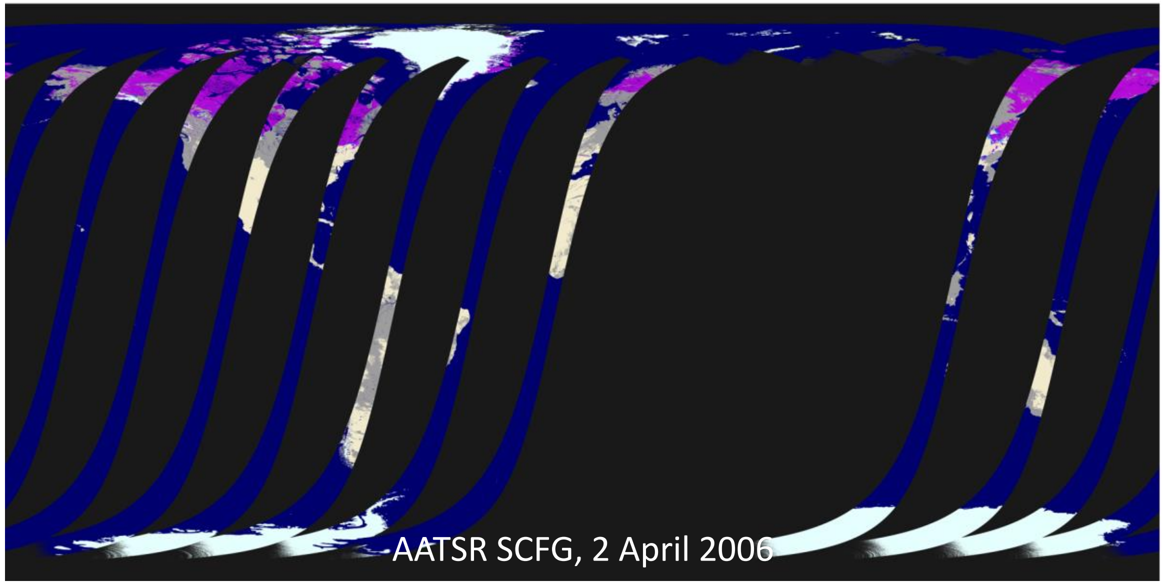
Comparison with other *snow_cci* products

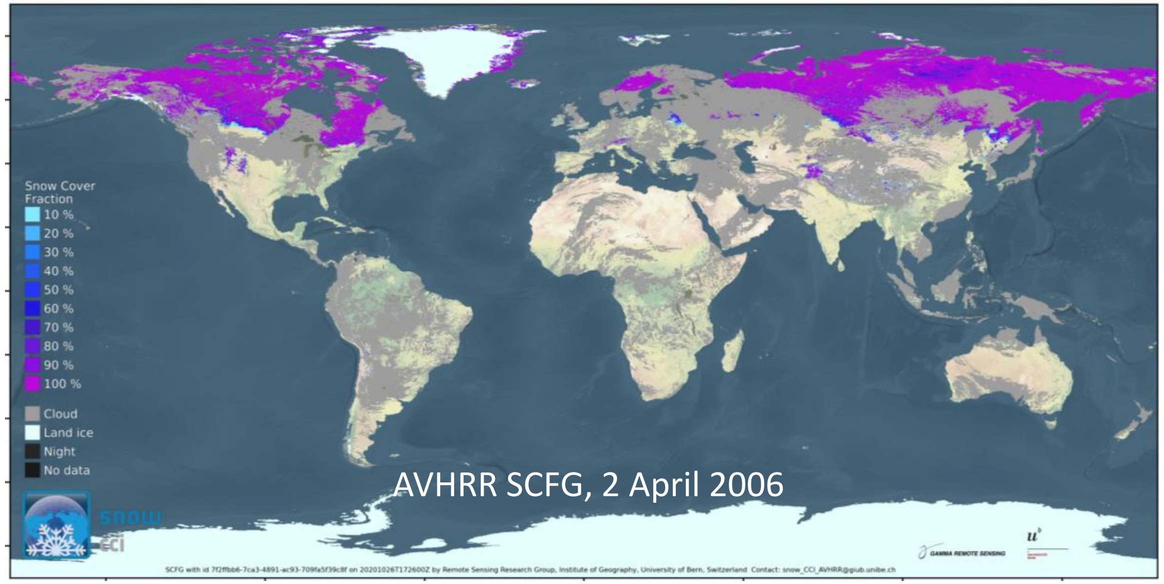


CryoClim FSC, 2 April 2006



MODIS SCFG, 2 April 2006


AATSR SCFG, 2 April 2006



AVHRR SCFG, 2 April 2006

Comparison with other *snow_cci* products

Summary **overall** comparison of the validation of the *snow_cci* CryoClim, MODIS and AVHRR FSCG products.

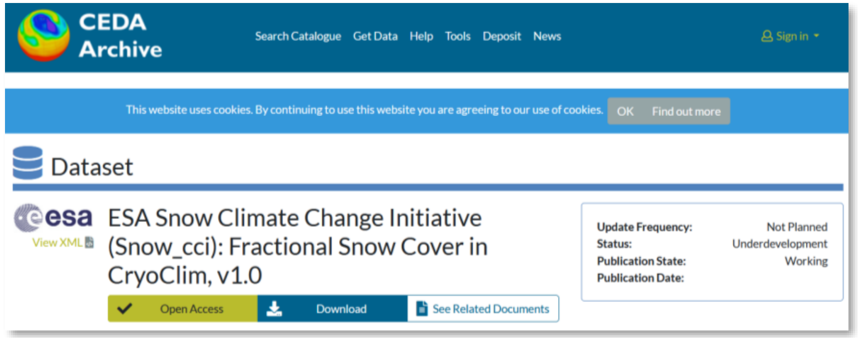
SCFG versus Salomonson HR	CryoClim FSC	MODIS FSC	AVHRR FSC
RMSE	15.50	15.65	18.10
Unbiased RMSE	15.32	15.65	17.29
Bias	2.38	0.34	-2.59
Correlation Coefficient	0.94	0.94	0.92

Summary and conclusions

- **Objective**: Based on the approach previously developed for retrieval of snow cover generating a binary approach, we have advanced the method to retrieve the fractional snow cover (FSC)
- **Approach**: The method uses a hidden Markov model (HMM) to model the states the seasonal snow cover goes through, as observed with optical and PMR data
- **Daily, all year full coverage**: The model fuses optical and PMR sensor data making possible retrieval of the full global area through all seasons independent of cloud cover and polar night
- **Binary validation**: Yearly overall accuracy mostly between 90 and 94%. Seasonal variation of monthly accuracies between 85 and 100%. The snow_cci CryoClim FSC product and the CryoClim SCE v. 2.0 binary product show very comparable results
- **Snow_cci baseline project validation**: using 543 Landsat scenes where snow maps were derived by three different retrieval algorithms. High overall accuracy with RMSE in the order of 16% and a bias lower than 2.4%. Separating open and forested areas, open areas gave 13-14% RMSE, and forested areas gave 17-18% RMSE.
- **Further development**: CryoClim development towards Sentinel-3 and CIMR. Substituting AVHRR with SLSTR and bridging the gap between SSMIS and CIMR with AMSR2/AMSR-3.

Snow CCI CryoClim FSC lat/lon product

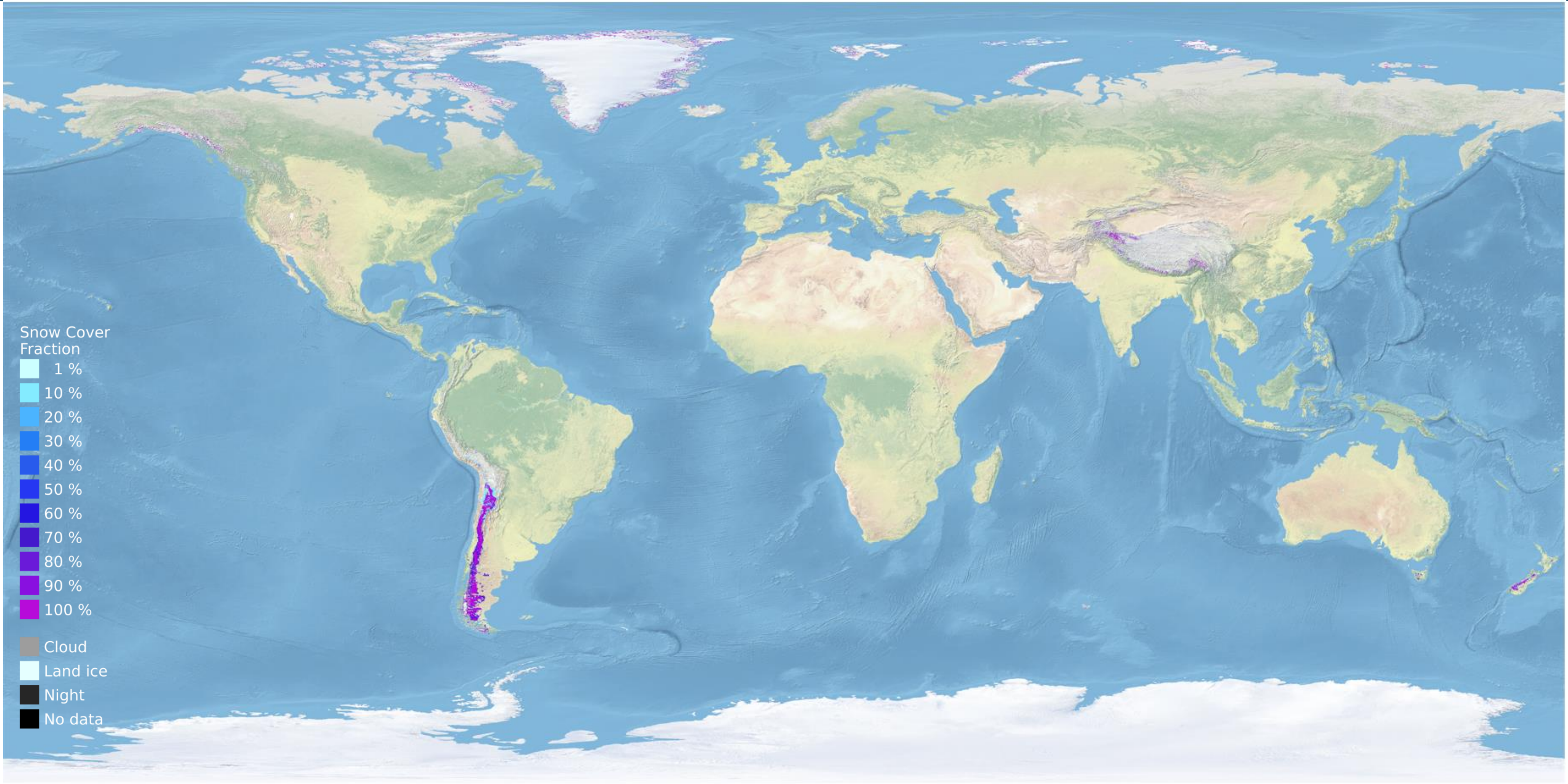
Subject	***Description***
Thematic variable	Fractional Snow Cover (FSC)
Retrieval algorithm	CryoClim multi-sensor/multi-temporal fusion of optical and PMR (Solberg et al. 2015; Rudjord et al. 2015) advanced in *snow_cci* to obtain FSC
Uncertainty algorithm	Salberg et al. 2021
Satellite(s)	NOAA-7, -9, -11, -14, -16, -18, -19; Nimbus-7, DMSP F8, - F11, - F13 and - F17
Sensor(s)	AVHRR, SMMR, SSM/I and SSMIS
Geographical domain(s)	Global
Temporal resolution	Daily
Start date time series	1 January 1982
End date time series	31 December 2020
Grid size	0.05°
Projection/datum	Geographical (lat/lon)/WGS 84
File format	NetCDF4, CF-v1.9
Product version	Prototype Version



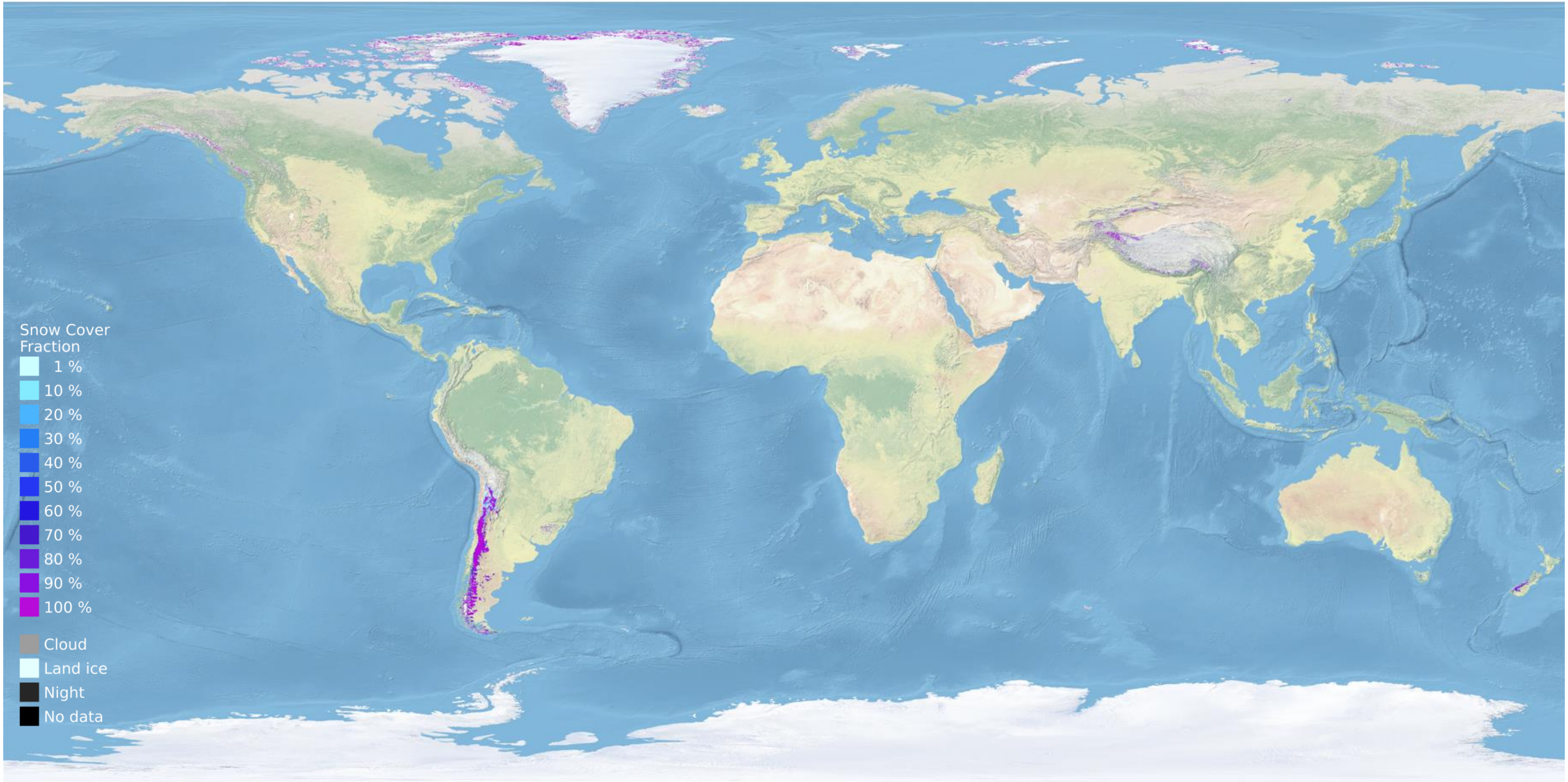

Thank you!

Extra slides

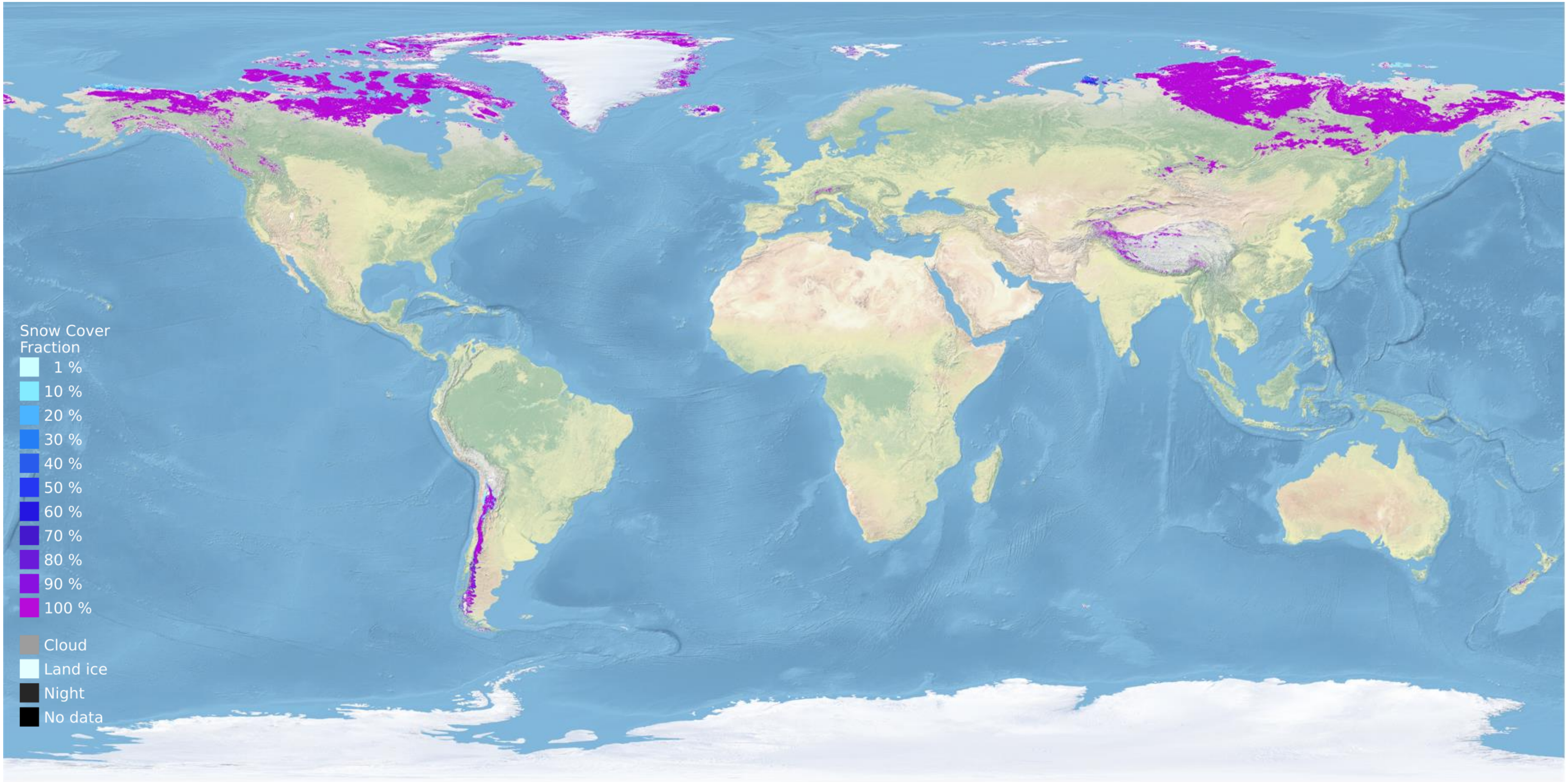
Example products: 2 August 2005



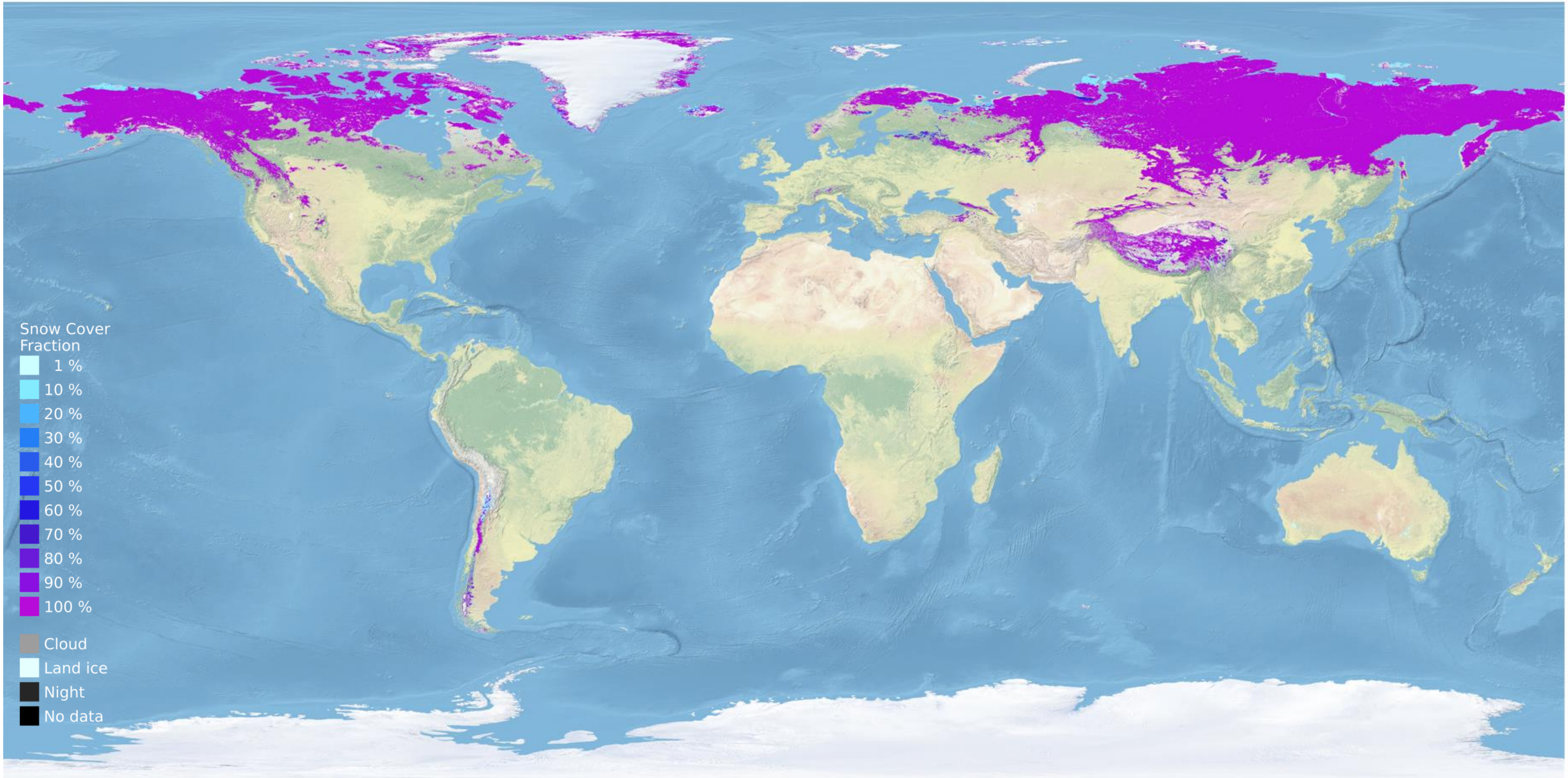
Example products: 2 September 2005



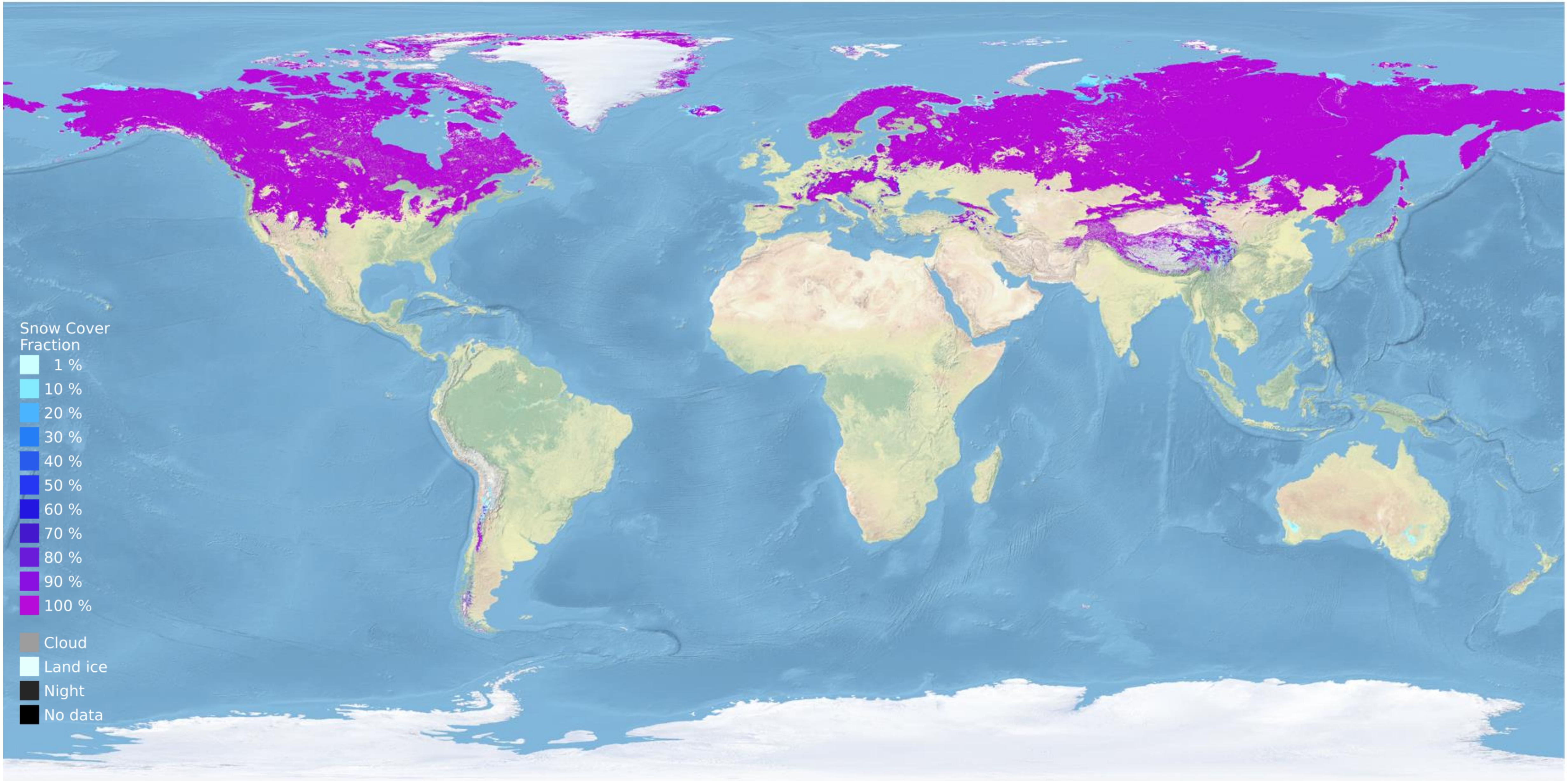
Example products: 2 October 2005



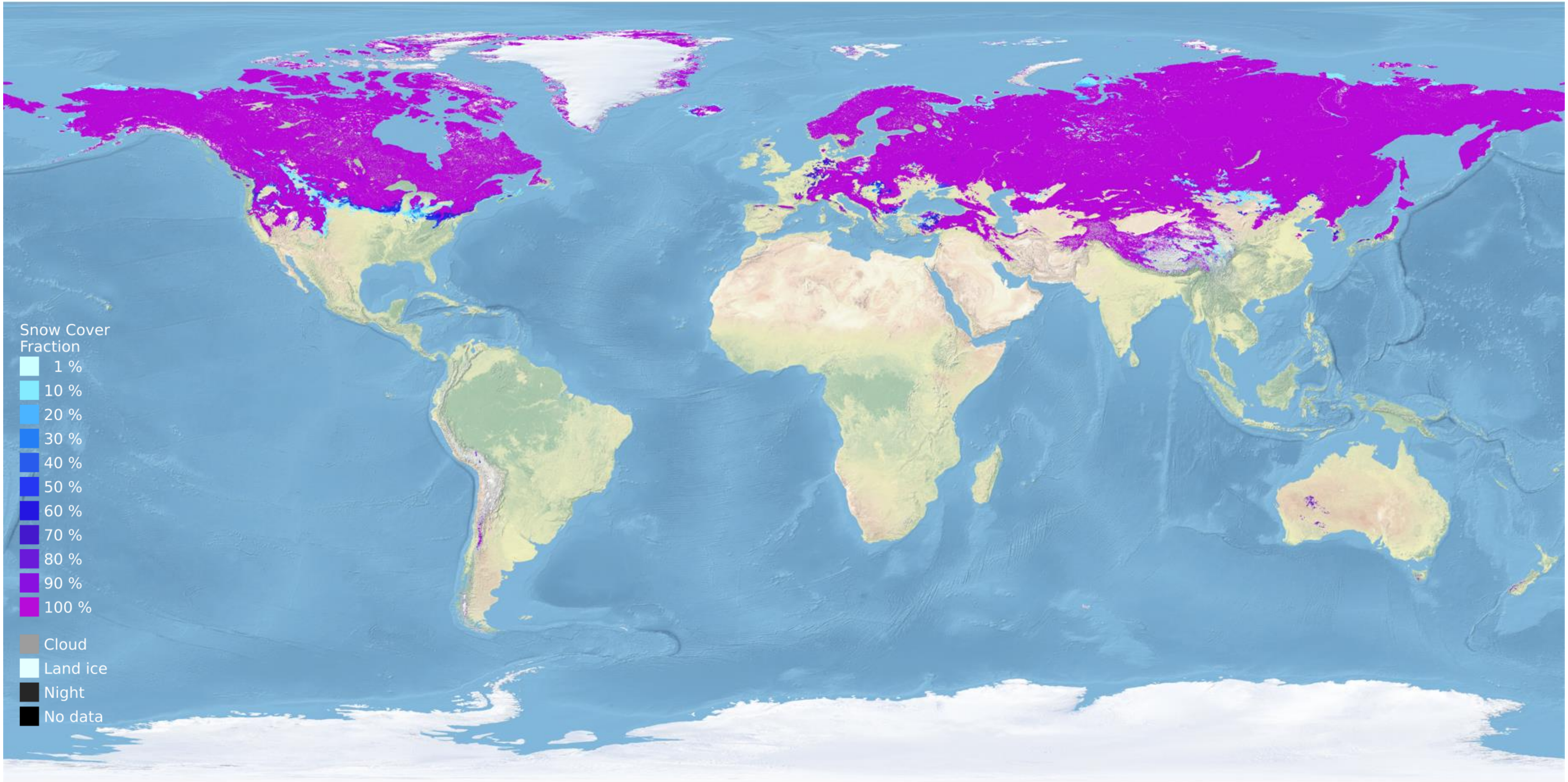
Example products: 2 November 2005



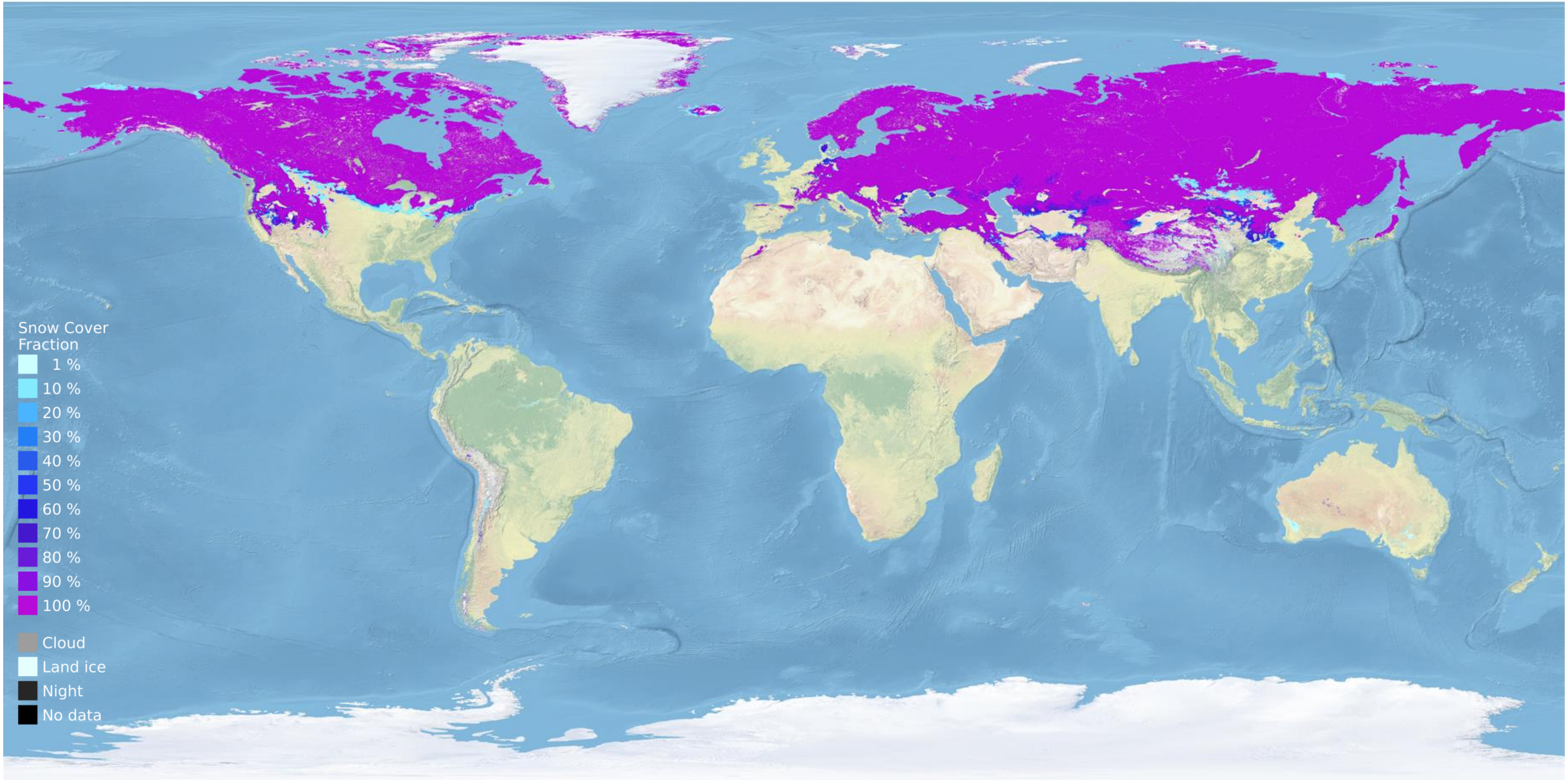
Example products: 2 December 2005



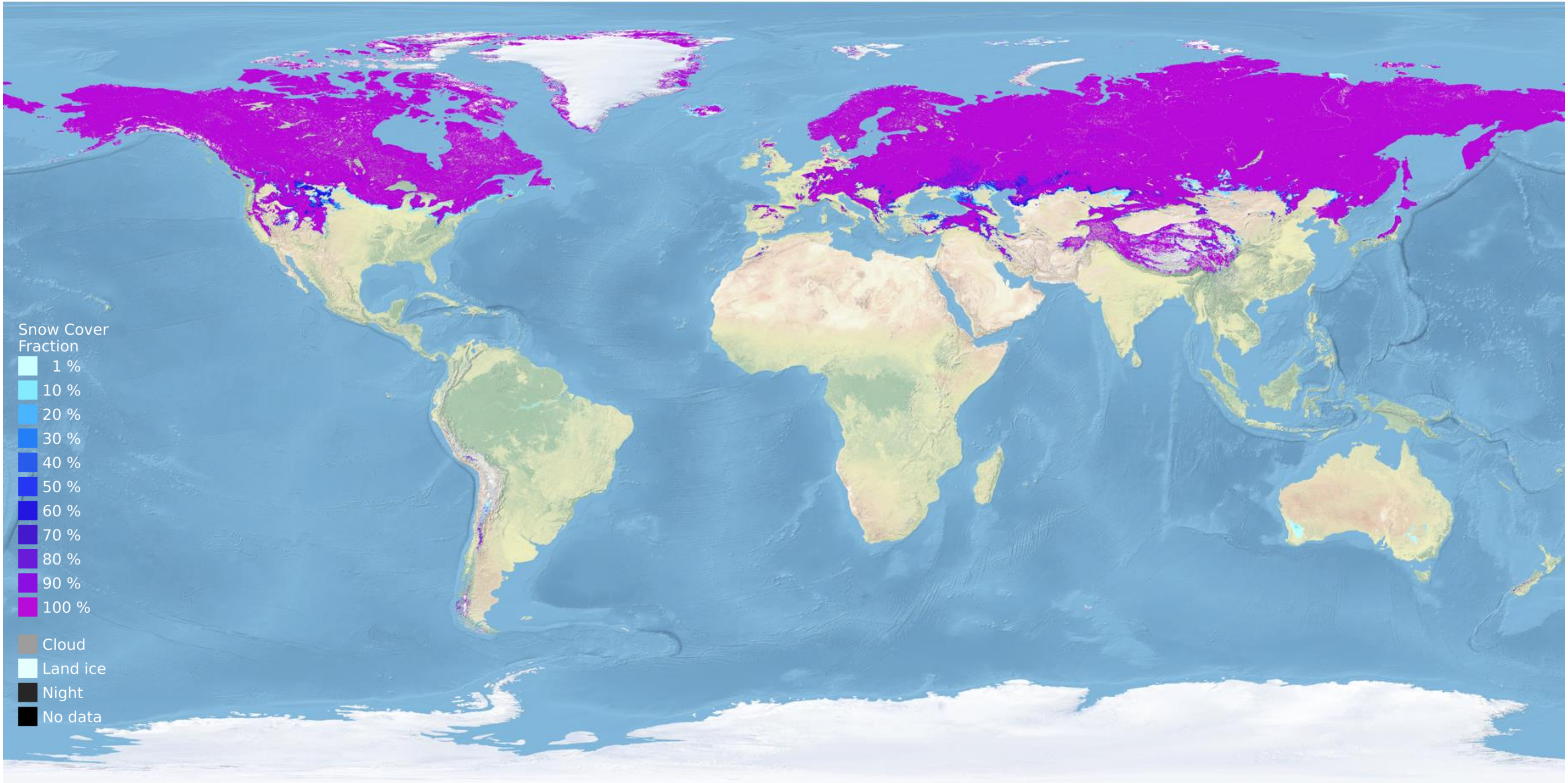
Example products: 2 January 2006



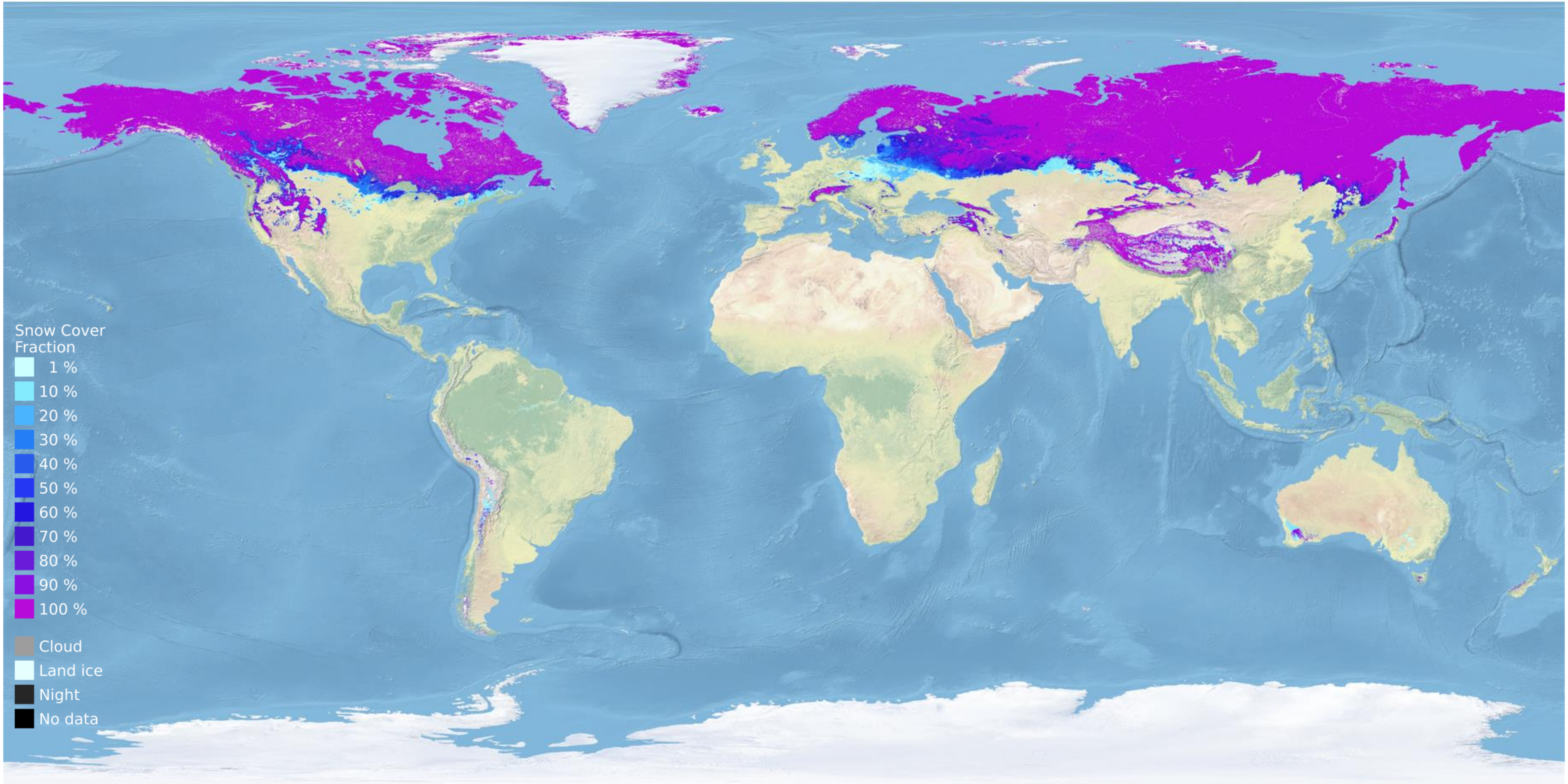
Example products: 2 February 2006



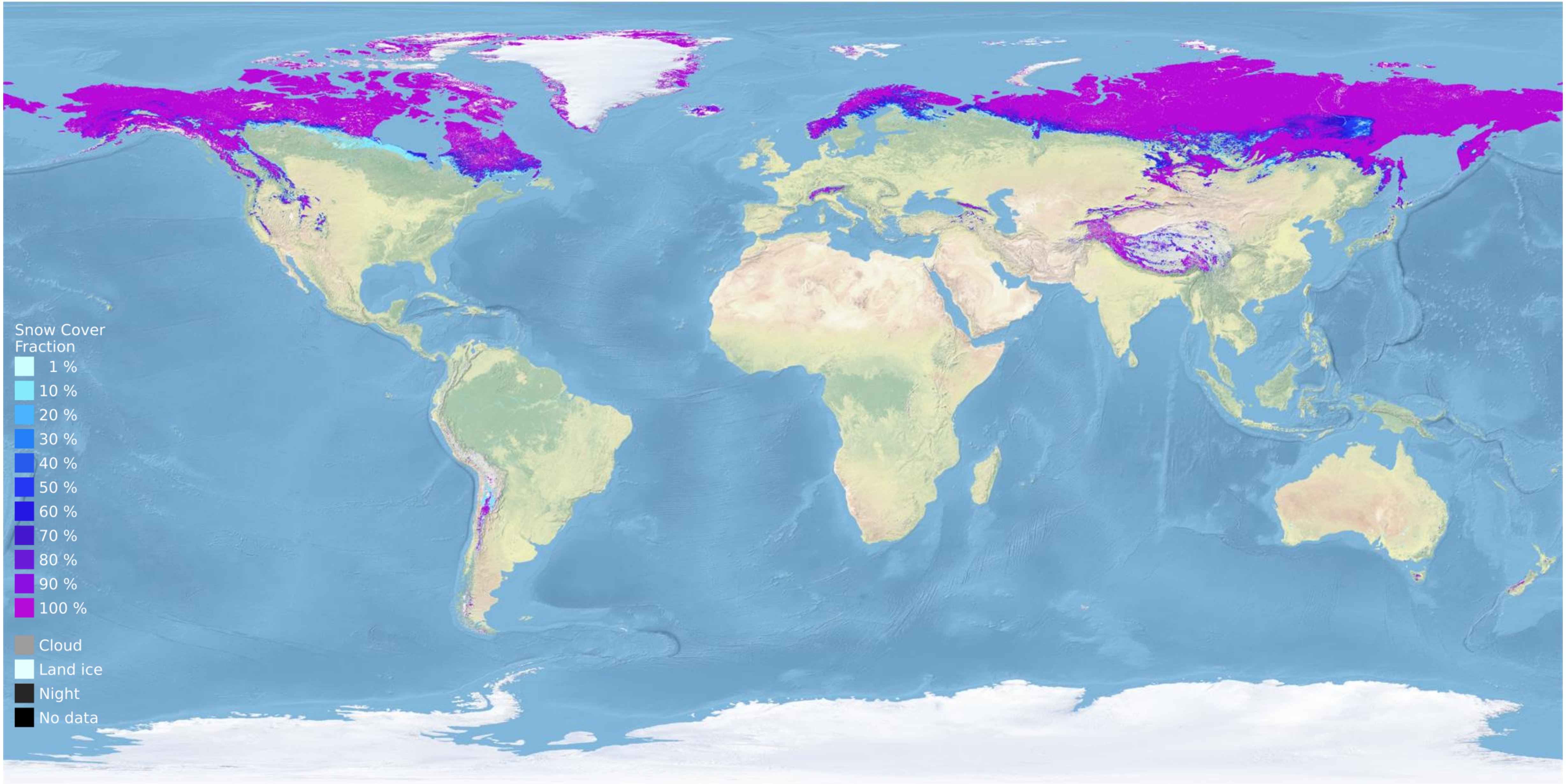
Example products: 2 March 2006



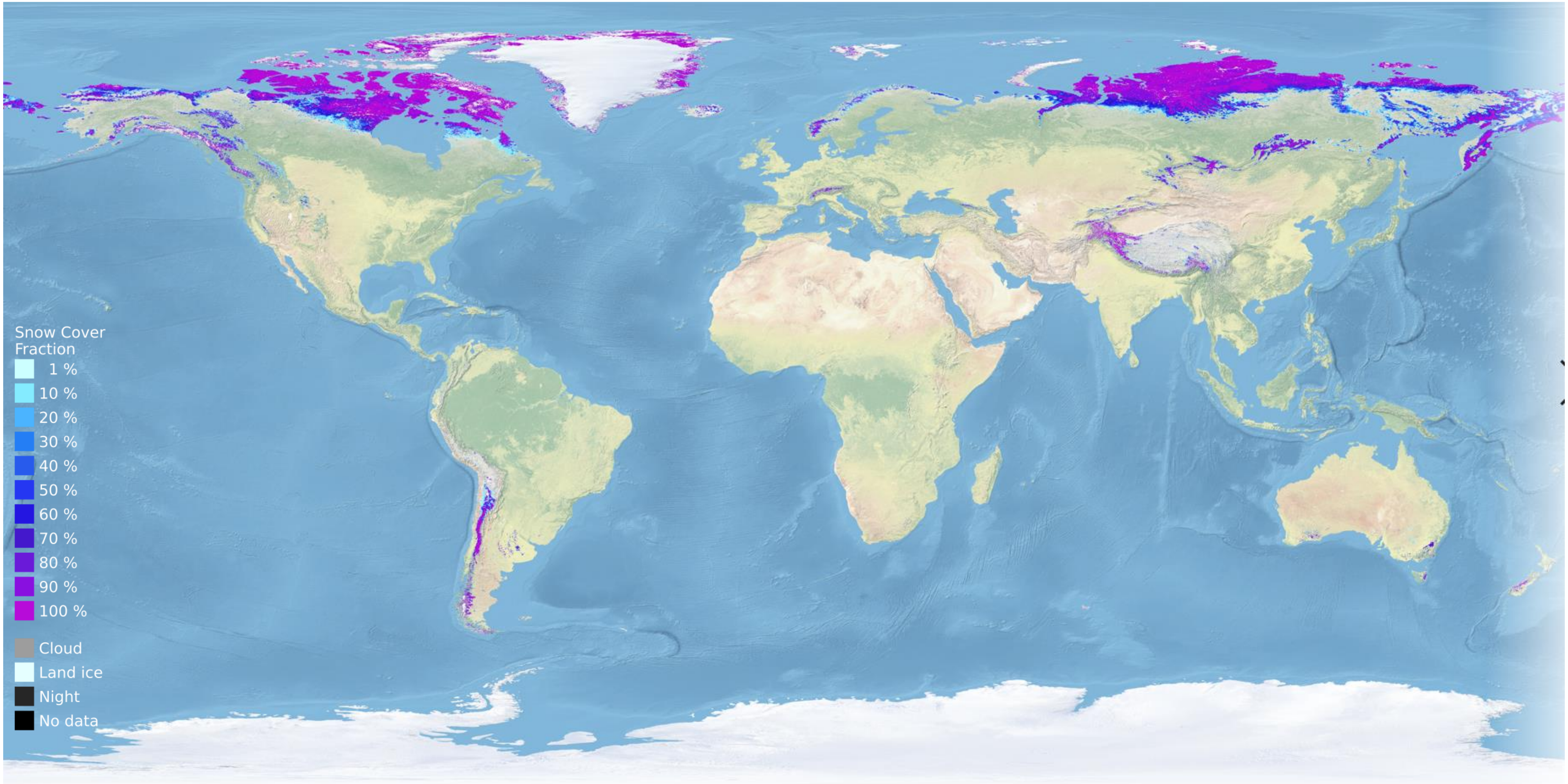
Example products: 2 April 2006



Example products: 2 May 2006



Example products: 2 June 2006



Example products: 2 July 2006