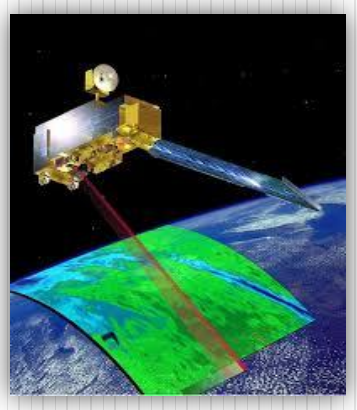
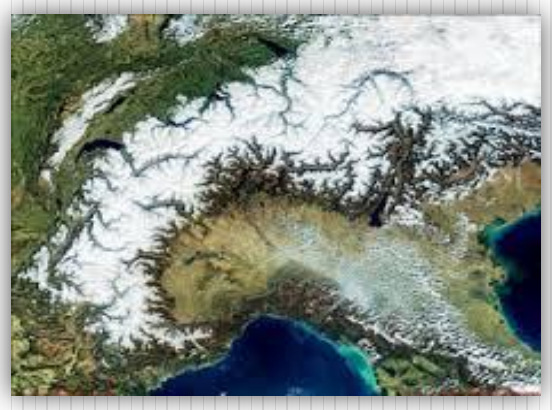
8th EARSeL Workshop on Land Ice & Snow
Remote Sensing of the Cryosphere: Past-Present-Future

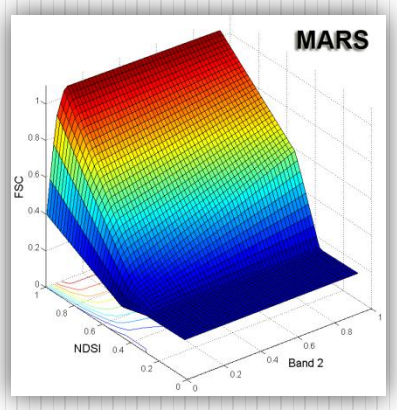
UNIVERSITÄT BERN

7-9 February 2017, Institute of Geography, University of Bern, Switzerland

FRACTIONAL SNOW COVER MAPPING FROM MODIS DATA OVER EUROPEAN ALPS BY MULTIVARIATE ADAPTIVE REGRESSION SPLINES







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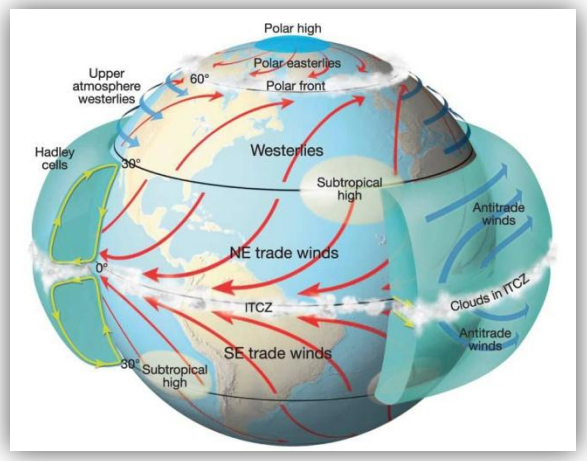
Outline

- Introduction
  - Significance of snow cover mapping
  - MODIS and snow cover mapping techniques
- Data Set and Methodology
  - Multivariate Adaptive Regression Splines (MARS)
  - Study area
  - Satellite imagery and preprocessing
  - Experimental design and performance measures
- Discussion of the Results
- Conclusion and Outlook

Introduction

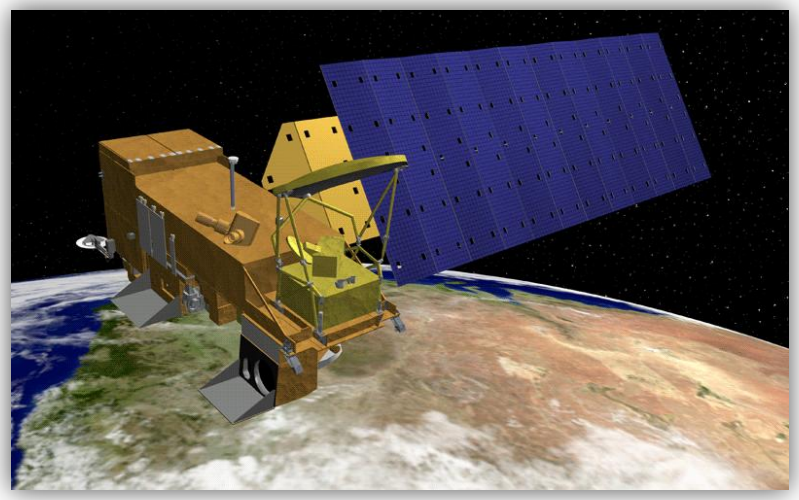
- Need for timely and accurate snow cover mapping:
  - May cover up to 40% of the Earth's surface,
  - Energy and water cycle of Earth,
  - High reflectance and low thermal conductivity,
  - A significant determinant of the Earth's radiation budget,
  - A vital source of irrigation and drinking water supply,
  - A major input component of General Circulation Models.

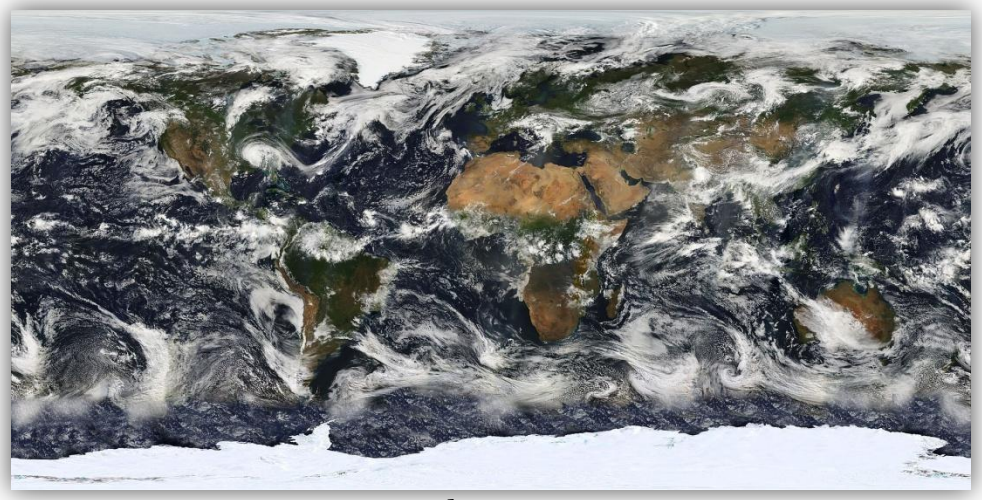




Introduction

- **MODIS** - Moderate Resolution Imaging Spectroradiometer
  - On board Terra since 1999 and on board Aqua since 2002, NASA
  - 36 spectral bands ranging from 0.4 µm to 14.4 µm
    at 250 m (1-2), 500 m (5-7) and 1000 m (8-36)
  - Large-scale global dynamics with 1-day temporal resolution





July 11, 2005

Introduction

- Snow cover mapping by Remote Sensing:
  - Binary Snow Mapping: "*Normalized Difference Snow Index*"

$$NDSI = \frac{Visible - SWIR}{Visible + SWIR} = \frac{band4_{MODIS} - band6_{MODIS}}{band4_{MODIS} + band6_{MODIS}}$$

Hall et al., 1995

MODIS band4: 0.545-0.565 µm
MODIS band6: 1.628-1.652 µm

NDSI ≥0.4 AND band2>11% AND band4 ≥10% = **Snow**

  - Subpixel Snow Mapping: *"Fractional Snow Cover"* - **FSC**
    - The exact location of the class fractions within each coarse resolution pixel: **Unknown**; **BUT**, the fractional class distribution may be well estimated..!
    - **1:** Linear Spectral Mixture Analysis, Painter et al., 2003; Sirguey et al., 2009; Zhu et al., 2012
    - **2:** Statistical linear relationship between NDSI and FSC in a MODIS pixel by using higher resolution Landsat snow maps as reference, Salomonson & Appel, 2004

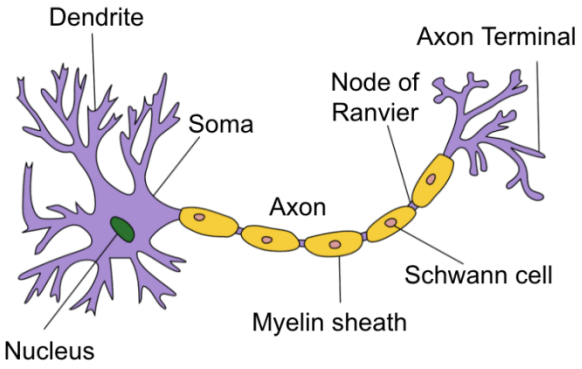
Introduction

- Snow cover mapping by Remote Sensing:
  - Subpixel Snow Mapping: *"Fractional Snow Cover"* - **FSC**
    - **3:** Artificial Neural Networks – **ANNs**.

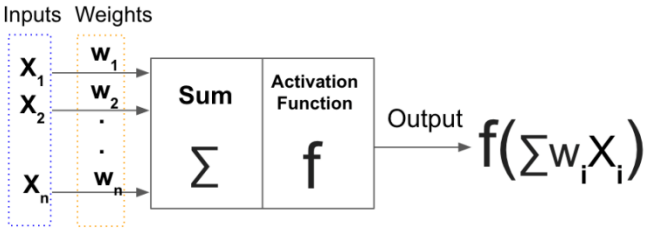
- **Dobreva, I. D. and Klein, A. G.** (2011). Fractional snow cover mapping through artificial neural network analysis of MODIS surface reflectance. ***Remote Sensing of Environment***, *115(12), pp. 3355-3366,*
- **Moosavi, V., Malekinezhad, H. and Shirmohammadi, B.** (2014). Fractional snow cover mapping from MODIS data using wavelet-artificial intelligence hybrid models. ***Journal of Hydrology***, *511, pp. 160-170,*
- **Czyzowska-Wisniewski, E. H., van Leeuwen, W. J. D., Hirschboeck, K. K., Marsh, S. E. and Wisniewski, W.T.** (2015). Fractional snow cover estimation in complex alpine-forested environments using an artificial neural network. ***Remote Sensing of Environment***, *156, pp. 403-417.*

Introduction

- Snow cover mapping by Remote Sensing:
  - Subpixel Snow Mapping: *"Fractional Snow Cover"* - **FSC**
    - **3:** Artificial Neural Networks – **ANNs**.
    - A machine learning algorithm that can generate an information processing model by resembling the knowledge acquisition mechanism of the brain from the environment.
    - A neural network can approximate highly nonlinear relationships between input variables and a target variable without requiring a priori knowledge of the nature of this relationship.



Structure of a typical neuron



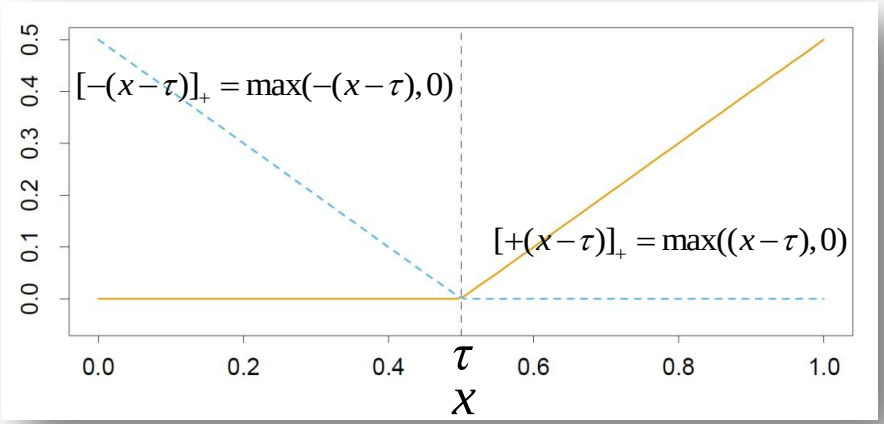
Structure of artificial neuron

Introduction

- Snow cover mapping by Remote Sensing:
  - Drawbacks of ANNs:
    - **Black Box**: Difficult to provide a comprehensible explanation of the process through which a given output has been obtained from a neural network.
    - No consensus opinion and related theory to determine the relative importance of the input variables.
    - **Complexity of model training:**
      - **Model Tuning Parameters:** Type of network, initial weights, number of hidden layers, number of neurons in each layer, type of learning algorithm, learning rate and momentum term, type of transfer functions…
      - **(*i*)** the number of parameters to be "tuned" are large, **(*ii*)** they highly depends on the type of specific application, and **(*iii*)** there exists no unique and explicit approach for choosing these parameters.
      - Basic ***trial-and-error*** approach to find optimal network parameters.

Data Set & Methodology

- **MARS** – Multivariate Adaptive Regression Splines
  - A state-of-the-art nonparametric regression procedure introduced by J. Friedman in 1991.
  - Expansions of the truncated piecewise linear functions:



Reflected pair

$$(x-\tau)_+ = \begin{cases} x-\tau, & \text{if } x > \tau, \\ 0, & \text{otherwise,} \end{cases}$$

$$(\tau-x)_+ = \begin{cases} \tau-x, & \text{if } x < \tau, \\ 0, & \text{otherwise.} \end{cases} \qquad x, \tau \in \mathbb{R}$$

- General model:

$$y = f(\boldsymbol{x}) + \varepsilon$$

- y : Response variable,
- $\boldsymbol{x} = (x_1, x_2, \ldots, x_p)^T$, vector of predictors,
- ε: observation error with zero mean and finite variance.

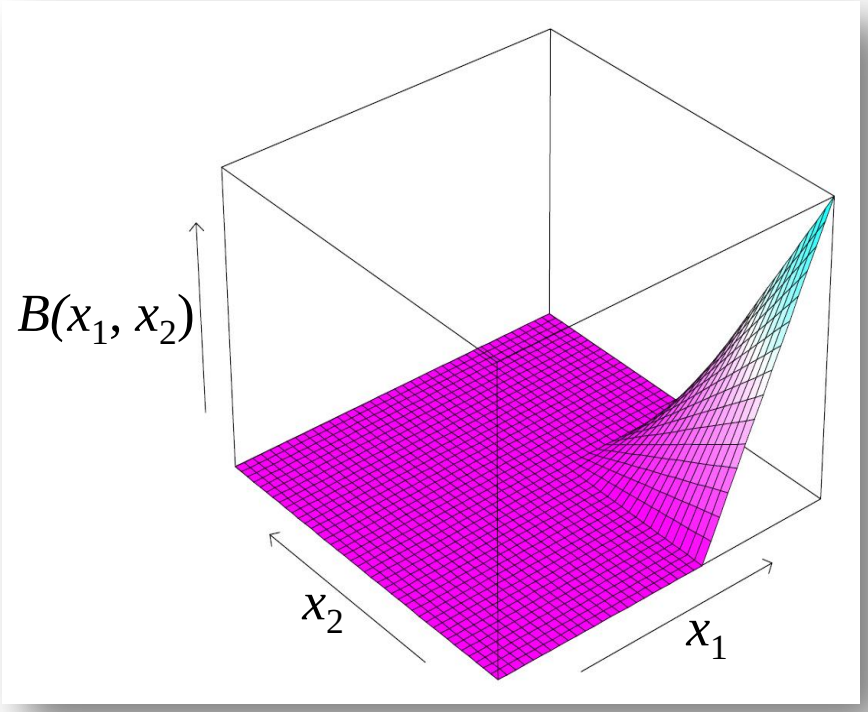
Data Set & Methodology

- **MARS** – Multivariate Adaptive Regression Splines
  - Can only piecewise linear functions be formed?
  - Reflected pairs can be multiplied together to form non-linear functions:

The function

$B(x_1, x_2) = (x_1\text{-}\tau_1)_+ \, (\tau_2\text{-}x_2)_+$

generated by the multiplication of two piecewise linear BFs of MARS (Hastie et al., 2009).



Data Set & Methodology

- **MARS** – Multivariate Adaptive Regression Splines

Tensor products of univariate spline functions → Spline fitting in higher dimensions

- Multivariate spline BFs: $B_m(\boldsymbol{x}) =: \prod_{j=1}^{K_m} \left[s_{\kappa_j^m} \cdot \left(x_{\kappa_j^m} - \tau_{\kappa_j^m} \right) \right]_+$

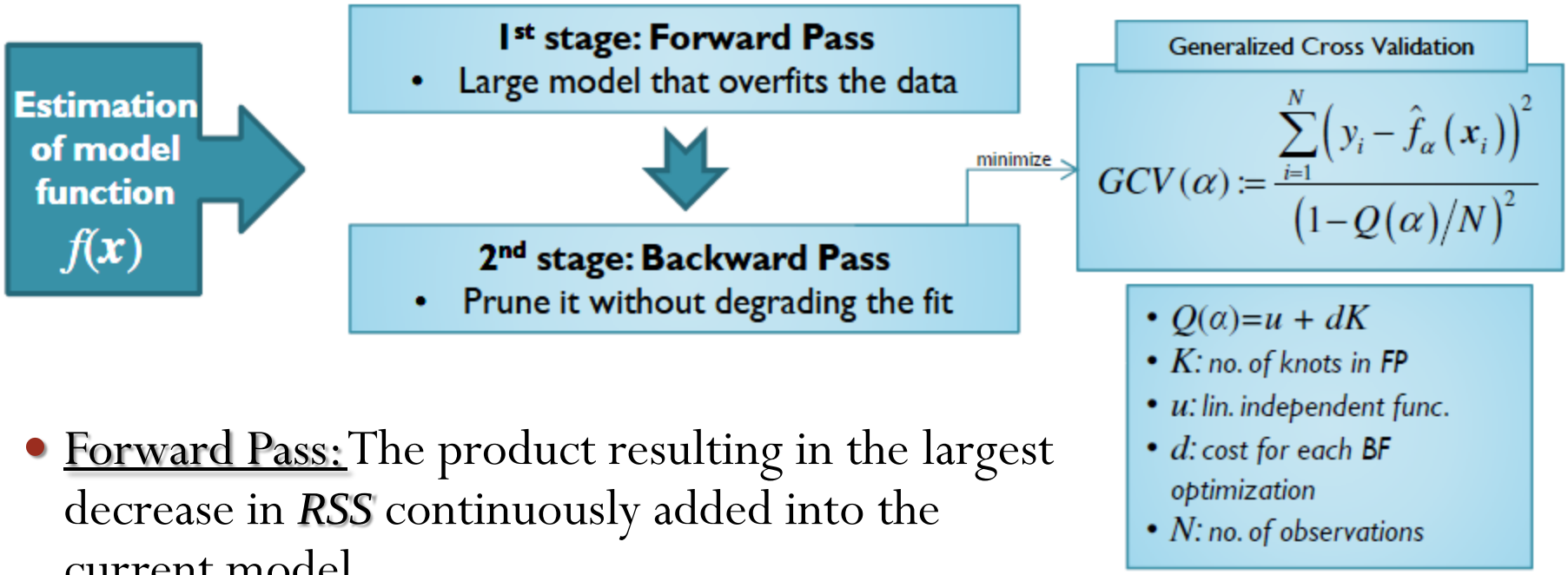
$$f(\boldsymbol{x}) = \beta_0 + \sum_{m=1}^{M} \beta_m B_m(\boldsymbol{x})$$

where

- K_m : total no. of truncated linear functions multiplied in the m^{th} BF,
- $x_{\kappa_j^m}$: input var. of the k^{th} truncated lin. function in the m^{th} BF,
- $\tau_{\kappa_j^m}$: knot value for $x_{K_j^m}$,
- $s_{\kappa_j^m} \in \{\pm 1\}$.

Data Set & Methodology

- **MARS** – Multivariate Adaptive Regression Splines

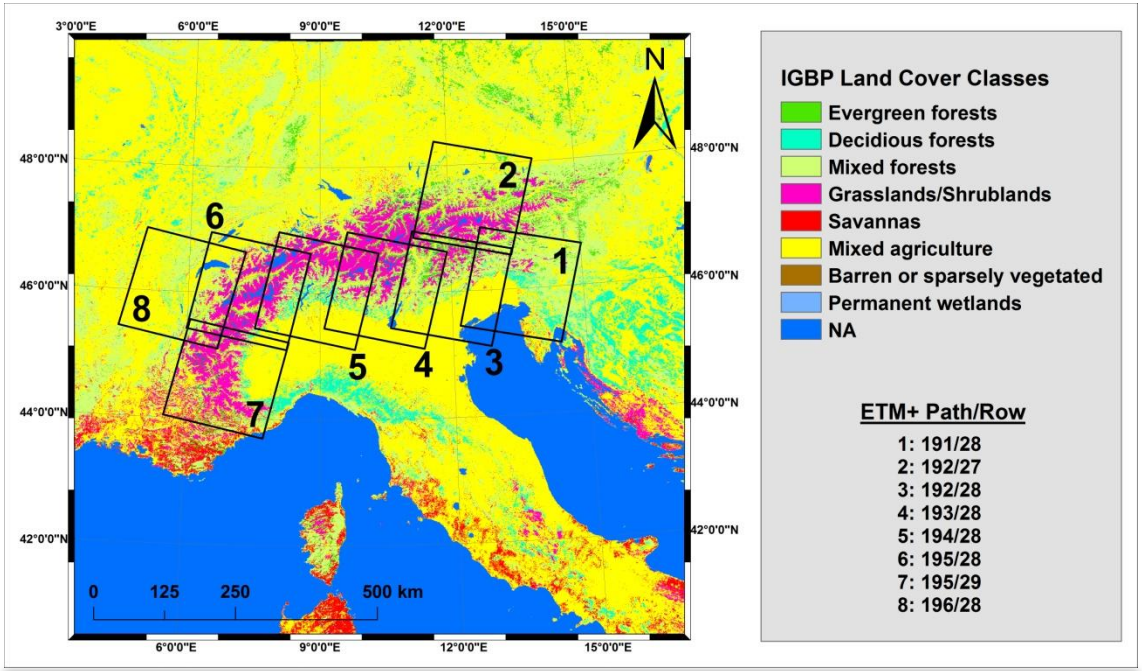


- Forward Pass: The product resulting in the largest decrease in *RSS* continuously added into the current model.

- Backward Pass: Removing BFs giving the smallest increase in *RSS*.

Data Set & Methodology

- Study area: European Alps



Location of ETM+ tiles and land cover classification image of 2003 according to the *International Geosphere-Biosphere Programme* (IGBP) provided in MODIS MCD12Q1 data. The seventeen original IGBP land cover classes are merged into eight.

Image Pair No	Date of Acquisition	Scene Times Landsat/MODIS	ETM+ Tile Path/Row
Training Image Set			
1	07.03.2000	09:57/10:35	193/28
2	21.03.2000	10:09/10:45	195/28
3	21.01.2001	09:55/10:30	193/28
4	07.12.2001	09:53/10:25	193/28
5	03.04.2002	10:11/10:40	196/28
6	25.01.2003	10:05/10:35	195/29
7	21.02.2003	09:47/10:15	192/28
8	28.02.2003	09:53/10:20	193/28
9	05.03.2003	10:11/10:40	196/28
10	18.03.2003	09:40/10:10	191/28
11	24.04.2003	09:59/10:25	194/28
Test Image Set			
A	08.04.2000	09:56/10:35	193/28
B	14.01.2001	09:48/10:25	192/27
C	15.02.2001	09:48/10:25	192/28
D	21.12.2001	10:05/10:35	195/29
E	23.03.2003	09:59/10:25	194/28

Data Set & Methodology

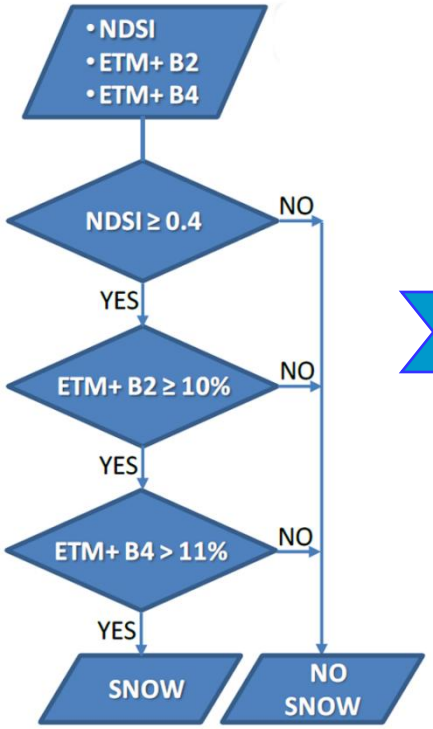
- Satellite Imagery:
  - Landsat 7 ETM+ and MODIS MOD02HKM pairs
  - ETM+ images before 31 May 2003 to avoid SLC failure issue
  - All MOD02HKM images re-projected to a UTM/WGS84

- Predictor variables (**Input**)
  - Reflectance values of MOD02HKM bands 1-7, NDSI, NDVI and IGBP land cover class

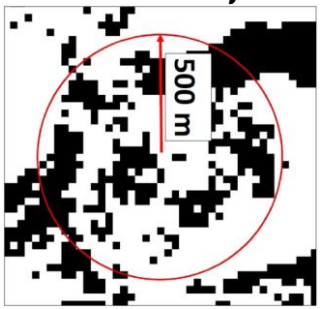
- Cloud, cloud shadow, water, bad quality pixels excluded by masks derived from the corresponding ancillary MODIS data

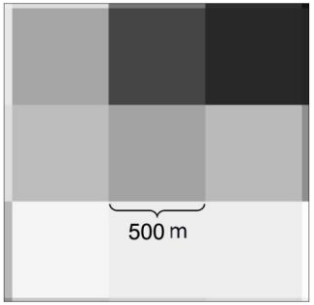
Data Set & Methodology

- Response variable (**Target**): % snow-covered area in a MODIS pixel
  - Binary snow maps derived from higher resolution ETM+ data:



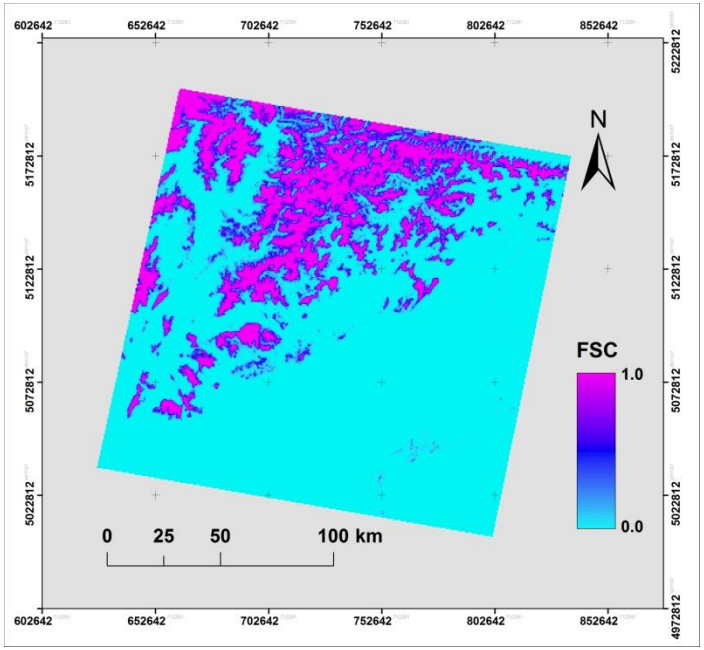
Landsat ETM+ Binary Snow Map





MODIS FSC Map

Test Scene C



Data Set & Methodology

- Training & Testing Data Sets

Image Pair No	Available Pixels	No. of Training Pixels
Combined Training Data		
1-11	651,721	13,033
Independent Test Image Set		
A	89,032	0
B	46,912	0
C	87,913	0
D	45,147	0
E	81,064	0
Combined	350,068	0

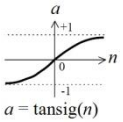
- After the exclusion of unsuitable pixels from the training set, **651,721** observations remained available to be sampled as training data.
- 2% of the available pixels by stratified random sampling (~**13,000** points).
- Stratification with respect to snow cover fraction from 0.0 to 1.0 with 0.1 intervals in order to prevent the MARS and the ANN models from being biased towards a certain snow cover fraction.

Data Set & Methodology

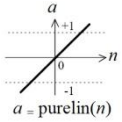
- **MARS Experimental Design**
  - Model tuning parameters for MARS:
    - Number of Basis Functions – maxBFs
    - Degree of interaction among predictor variables – maxDG
  - Basic **trial-and-error** methodology
    - Various settings for maxBFs and maxDG
    - maxBFs :[20, 40,…,200] and,
    - maxDG: [1, 2, 3]
  - Training Data: 70% for model training, 30% for model validation
    - MARS model with best validation performance
  - MARS model performance on 5 independent test scenes and a combined set

Data Set & Methodology

- **ANN Experimental Design**
  - Network properties for ANN:
    - Feed-forward network trained with backpropagation
    - Learning algorithm: Gradient-based Levenberg-Marquardt
    - Number of input nodes: 10, Number of hidden layers: 1, Number of output nodes: 1
    - Transfer function in the hidden layer: *Hyperbolic tangent*



    - Transfer function in the output layer: *Linear*



  - Basic **trial-and-error** methodology
    - Various settings for the number of neurons in the hidden layer
    - No of neurons: [7,10,13,16,19,22,25] and,
  - Training Data: 70% for model training, 15% for model validation, 15% for testing during the training phase

Data Set & Methodology

- Performance measures
  - Root-mean-square-error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{N}}$$

N : Total number of observations,
y_i : The ith reference value,
$\hat{y}_i$: The ith predicted value.

  - Pearson's correlation coefficient:

$$R = \frac{N\sum_{i=1}^{N} y_i \hat{y}_i - \sum_{i=1}^{N} y_i \sum_{i=1}^{N} \hat{y}_i}{\sqrt{N\sum_{i=1}^{N} y_i^2 - \left(\sum_{i=1}^{N} y_i\right)^2}\sqrt{N\sum_{i=1}^{N} \hat{y}_i^2 - \left(\sum_{i=1}^{N} \hat{y}_i\right)^2}}$$

Discussion of the Results

- Optimal model training parameters:

Division of Training Data			
	Training	Validation	**Testing**
MARS	70%	-	**30%**
ANN	70%	15%	**15%**

  - MARS: maxBFs = 20 and maxDG = 3 with

$R = 0.97, RMSE = 0.0881,$

  - ANN: no. of neurons in the hidden layer = 13 with

$R = 0.97, RMSE = 0.0856.$

Discussion of the Results

- Overall results in terms of *R* and *RMSE*:

	No. of Pixels	ANN FSC		MARS FSC		MOD10 FSC	
		R	*RMSE*	*R*	*RMSE*	*R*	*RMSE*
Training Data	13,033	0.97	0.084	0.97	0.086	0.95	0.129
Test Comb.	350,068	0.94	0.141	0.95	0.125	0.93	0.167
Test A	89,032	0.94	0.169	0.98	0.106	0.98	0.095
Test B	46,912	0.71	0.203	0.72	0.198	0.60	0.299
Test C	87,913	0.94	0.100	0.95	0.092	0.92	0.147
Test D	45,147	0.93	0.153	0.93	0.165	0.89	0.201
Test E	81,064	0.98	0.084	0.97	0.087	0.96	0.109

Discussion of the Results

- Behaviour at low-, mid- and high-FSC values:

		Test A	Test B	Test C	Test D	Test E
Landsat FSC	Total Pixels/%	89,032/100	46,912/100	87,913/100	45,147/100	81,064/100
	Low FSC/%	61,052/69	5,526/12	72,614/83	29,424/65	64,249/79
	Mid FSC/%	3,896/4	12,207/26	6,764/8	5,689/13	3,908/5
	High FSC/%	24,084/27	29,179/62	8,535/9	10,034/22	12,907/16
ANN FSC	Low FSC/%	66,118//74	1,989/4	72,196/82	31,033/69	64,617/79
	Mid FSC/%	16,806/19	17,005/36	9,309/11	12,002/27	3,002/4
	High FSC/%	6,108/7	27,918/60	6,408/7	2,112/4	13,445/17
MARS FSC	Low FSC/%	61,459/69	2,988/6	71,200/81	29,478/65	63,246/78
	Mid FSC/%	5,572/6	16,738/36	8,771/10	11,628/26	3,719/5
	High FSC/%	22,001/25	27,192/58	7,942/9	4,041/9	14,099/17
MOD10 FSC	Low FSC/%	61,590/69	5,835/12	71,818/82	28,707/64	64,821/80
	Mid FSC/%	2,402/3	2,241/5	2,516/3	2,393/5	1,723/2
	High FSC/%	25,040/28	38,836/83	13,579/15	14,047/31	14,520/18

- Low-FSC: FSC < 0.3,
- Mid-FSC: 0.3 ≤ FSC ≤ 0.7,
- High_FSC: FSC > 0.7.

Overestimate

Underestimate

Welldone!

± 3 %

Discussion of the Results

- The MARS model:

INTERCEPT = - 0.06857
BF1 = max(0, NDSI - 0.46436)
BF2 = max(0, 0.46436 - NDSI)
BF3 = BF1 * max(0, BAND2 - 0.10048)
BF4 = BF1 * max(0, 0.10048 - BAND2)
BF5 = max(0, BAND3 - 0.04123)
BF6 = max(0, 0.04123 - BAND3)
BF7 = max(0, BAND7 - 0.0093083)
BF8 = max(0, 0.0093083 - BAND7)
BF9 = BF3 * max(0, BAND4 - 0.14008)
BF10 = BF3 * max(0, 0.14008 - BAND4)
BF11 = max(0, NDSI - 0.29086)
BF12 = max(0, 0.29086 - NDSI)
BF13 = BF11 * max(0, BAND2 - 0.052862)
BF14 = BF11 * max(0, 0.052862 - BAND2)
BF15 = max(0, BAND4 - 0.24768)
BF16 = max(0, 0.24768 - BAND4)
BF17 = max(0, LAND COVER - 5)
BF18 = max(0, 5 - LAND COVER)
BF19 = BF18 * max(0, BAND3 - 0.35229)
BF20 = BF18 * max(0, 0.35229 - BAND3)

$$Y = -0.06857 + 1.3311*BF1 - 0.38379*BF2 - 2.9602*BF3 - 2.7908*BF4 + 1.6644*BF5 - 0.95273*BF6 - 14.397*BF8 - 0.92949*BF9 + 166.03*BF10 + 0.39869*BF12 + 2.4327*BF13 - 11.837*BF14 - 1.5434*BF15 + 0.83337*BF16 - 0.033686*BF17 - 0.074036*BF18 + 0.23212*BF19 + 0.19314*BF20$$

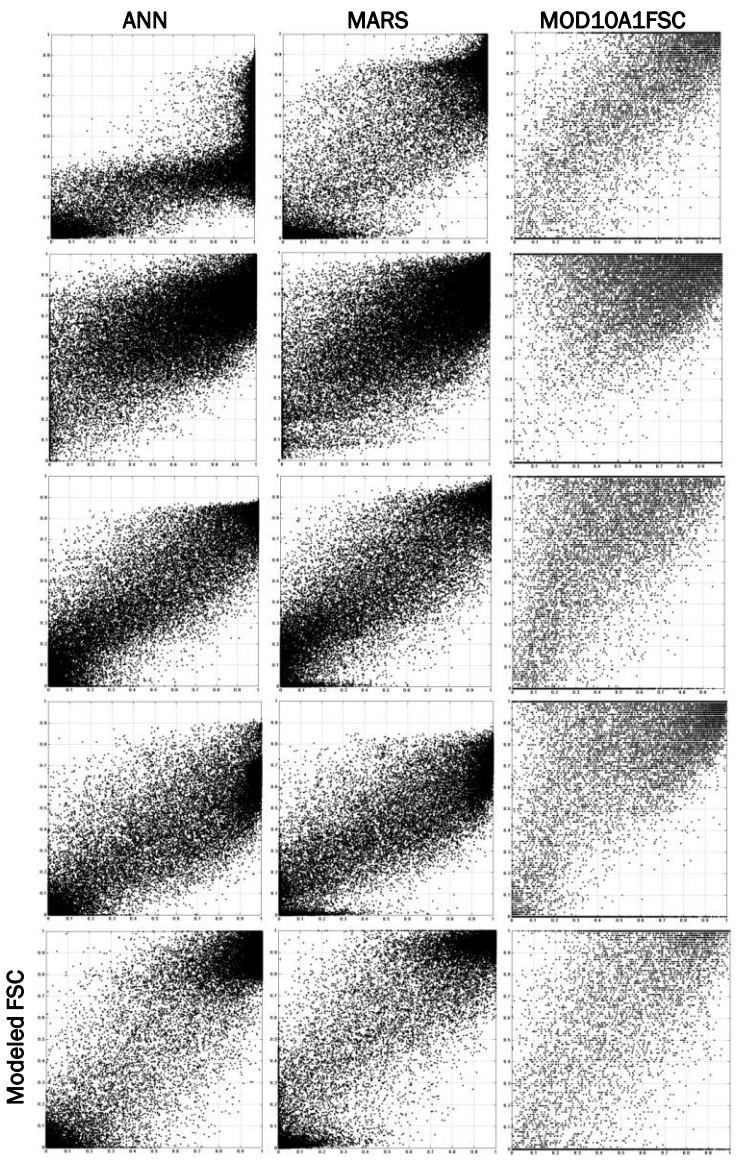
- Number of selected BFs after the bacward pass: 18
- Number of terms at each degree of interaction: 10, 6, 2

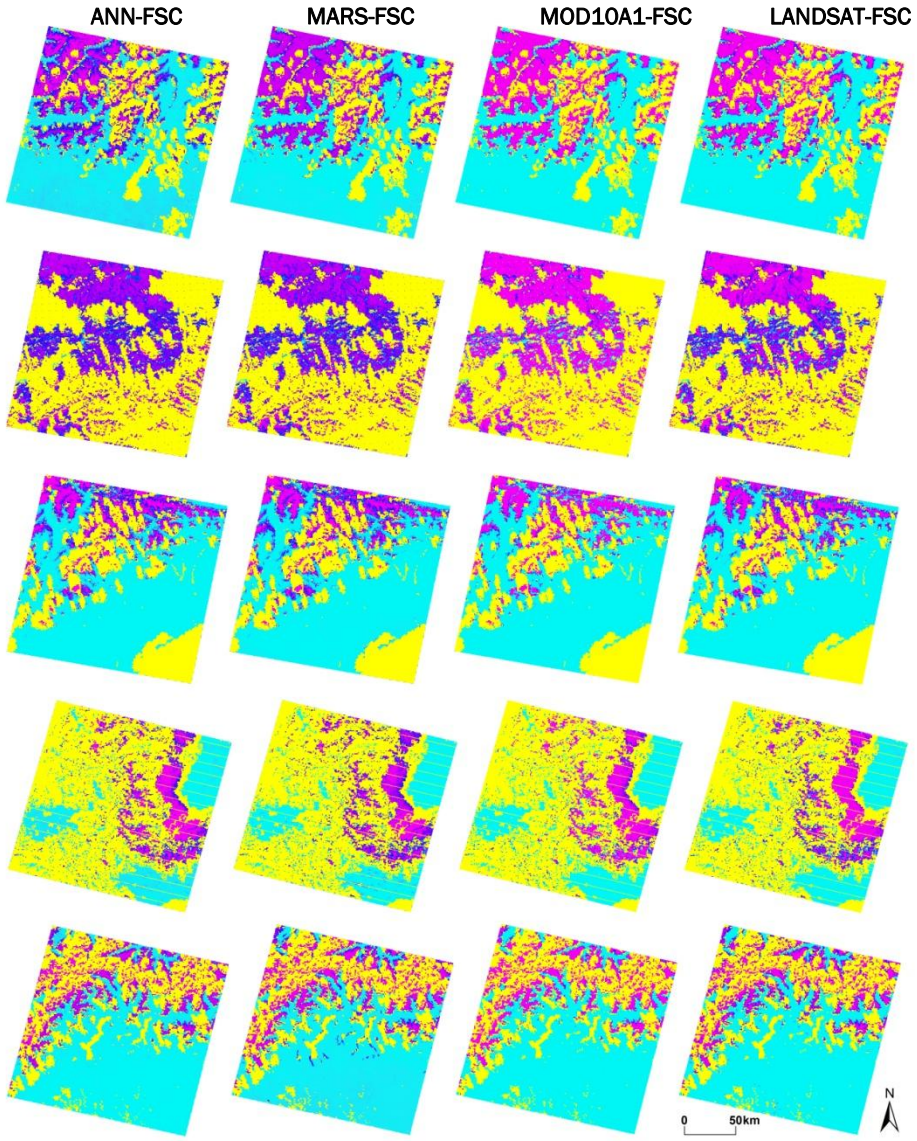
VARIABLE IMPORTANCE:

NDSI, BAND2, BAND3, BAND4, LAND COVER, BAND7
*BANDS 1, 5, 6 & NDVI: NOT INCLUDED IN THE FINAL MARS MODEL

Discussion of the Results

- Scatter plots & FSC maps:





Conclusion & Outlook

- The spatial and temporal distribution of snow is important.
- A surface condition that affects radiation and water balance calculations which are inputs to hydrological cycle and climate studies.
- Promising results in FSC mapping by MARS:
  - With its elaborately designed mathematical structure and simplicity in model building, MARS is a strong alternative to ANNs for estimating percentage snow-covered area.

Conclusion & Outlook

- Potential future directions:
  - Detailed investigation on the impact of ANNs' model building parameters on FSC estimation,
  - Support Vector Regression (SVR) for FSC mapping,
  - New version of MARS to estimate FSC:
    - **Conic MARS** (**CMARS**): Originated from the ***Theory of Inverse Problems*** and powered by the modern methods of ***Continuous Optimization***, Weber et al., 2011
  - Mutual comparison of MARS, CMARS, ANNs & SVR.

References

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Thank You...



