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
Introduction

- Snow cover mapping by Remote Sensing:
  - Binary Snow Mapping: “Normalized Difference Snow Index”
    \[
    \text{NDSI} = \frac{\text{Visible} - \text{SWIR}}{\text{Visible} + \text{SWIR}} = \frac{\text{band4}_{\text{MODIS}} - \text{band6}_{\text{MODIS}}}{\text{band4}_{\text{MODIS}} + \text{band6}_{\text{MODIS}}} \]
    MODIS band4: 0.545-0.565 µm
    MODIS band6: 1.628-1.652 µm
    NDSI ≥0.4 AND band2 > 11% AND band4 ≥10% = Snow
    Hall et al., 1995

- 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,
  - 2: Statistical linear relationship between NDSI and FSC in a MODIS pixel by using higher resolution Landsat snow maps as reference,
    Painter et al., 2003; Sirguey et al., 2009; Zhu et al., 2012
    Salomonson & Appel, 2004
Introduction

• Snow cover mapping by **Remote Sensing:**

  • Subpixel Snow Mapping: “**Fractional Snow Cover**” - **FSC**
  
  3: Artificial Neural Networks – **ANNs**.


Introduction

- Snow cover mapping by **Remote Sensing**:
- Subpixel Snow Mapping: **“Fractional Snow Cover”** - FSC
  - 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](image1)

![Structure of artificial neuron](image2)
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 depend 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
  - Expansions of the truncated piecewise linear functions:

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

- General model:
  \[
  y = f(x) + \varepsilon
  \]

- **y**: Response variable,
- **x = (x_1, x_2, ..., x_p)^T**, vector of predictors,
- **\varepsilon**: 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

\[ B(x_1, x_2) = (x_1 - \tau_1)_+ (\tau_2 - x_2)_+ \]

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

- **MARS** – Multivariate Adaptive Regression Splines

**Multivariate spline BFs:**

\[
B_m(x) = \prod_{j=1}^{K_m} \left[ s_{\kappa_j^m} \cdot \left( x_{\kappa_j^m} - \tau_{\kappa_j^m} \right) \right] +
\]

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

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 \( x_{\kappa_j^m} \),
- \( s_{\kappa_j^m} \in \{ \pm 1 \} \).
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**.

**Generalized Cross Validation**

\[
GCV(\alpha) := \frac{\sum_{i=1}^{N} (y_i - \hat{f}_\alpha(x_i))^2}{(1 - Q(\alpha)/N)^2}
\]

- \(Q(\alpha) = u + dK\)
- \(K\): no. of knots in **FP**
- \(u\): lin. independent func.
- \(d\): cost for each BF optimization
- \(N\): no. of observations
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.

<table>
<thead>
<tr>
<th>Image Pair No</th>
<th>Date of Acquisition</th>
<th>Scene Times Landsat/MODIS</th>
<th>ETM+ Tile Path/Row</th>
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<td>193/28</td>
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<td>B</td>
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<td>D</td>
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<td>09:59/10:25</td>
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<td>E</td>
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</table>
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:
Data Set & Methodology

• Training & Testing Data Sets

<table>
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<tr>
<th>Image Pair No</th>
<th>Available Pixels</th>
<th>No. of Training Pixels</th>
</tr>
</thead>
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<tr>
<td>1-11</td>
<td>651,721</td>
<td>13,033</td>
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<tr>
<td>Independent Test Image Set</td>
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<tr>
<td>A</td>
<td>89,032</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>46,912</td>
<td>0</td>
</tr>
<tr>
<td>C</td>
<td>87,913</td>
<td>0</td>
</tr>
<tr>
<td>D</td>
<td>45,147</td>
<td>0</td>
</tr>
<tr>
<td>E</td>
<td>81,064</td>
<td>0</td>
</tr>
<tr>
<td>Combined</td>
<td>350,068</td>
<td>0</td>
</tr>
</tbody>
</table>

• 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 – $\text{maxBFs}$
  - Degree of interaction among predictor variables – $\text{maxDG}$

- Basic **trial-and-error** methodology
  - Various settings for $\text{maxBFs}$ and $\text{maxDG}$
  - $\text{maxBFs} : [20, 40, \ldots, 200]$ and,
  - $\text{maxDG} : [1, 2, 3]$

- 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 \(i\)th reference value,
    \(\hat{y}_i\): The \(i\)th 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:

<table>
<thead>
<tr>
<th>Division of Training Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
</tr>
<tr>
<td>MARS</td>
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<tr>
<td>ANN</td>
</tr>
</tbody>
</table>

- MARS: maxBFs = 20 and maxDG = 3 with
  \[ R = 0.97, \text{RMSE} = 0.0881, \]
- ANN: no. of neurons in the hidden layer = 13 with
  \[ R = 0.97, \text{RMSE} = 0.0856. \]
Discussion of the Results

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

<table>
<thead>
<tr>
<th>No. of Pixels</th>
<th>ANN FSC</th>
<th>MARS FSC</th>
<th>MOD10 FSC</th>
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<td>$R$</td>
<td>RMSE</td>
<td>$R$</td>
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<td>Training Data</td>
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<td>Test A</td>
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<tr>
<td>Test B</td>
<td>46,912</td>
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<td>Test C</td>
<td>87,913</td>
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<td>Test D</td>
<td>45,147</td>
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<td>Test E</td>
<td>81,064</td>
<td>0.98</td>
<td>0.084</td>
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## Discussion of the Results

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

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<th>Test A</th>
<th>Test B</th>
<th>Test C</th>
<th>Test D</th>
<th>Test E</th>
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<td><strong>Total Pixels/%</strong></td>
<td><strong>Low FSC/%</strong></td>
<td><strong>Mid FSC/%</strong></td>
<td><strong>High FSC/%</strong></td>
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<td>12,907/16</td>
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<td><strong>ANN FSC</strong></td>
<td><strong>Low FSC/%</strong></td>
<td><strong>Mid FSC/%</strong></td>
<td><strong>High FSC/%</strong></td>
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<td>Low FSC/%</td>
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<td>High FSC/%</td>
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<tr>
<td><strong>MARS FSC</strong></td>
<td><strong>Low FSC/%</strong></td>
<td><strong>Mid FSC/%</strong></td>
<td><strong>High FSC/%</strong></td>
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</table>

- **Landsat FSC:**
  - **Low-FSC:** $FSC < 0.3$,
  - **Mid-FSC:** $0.3 \leq FSC \leq 0.7$,
  - **High-FSC:** $FSC > 0.7$.

- **ANN FSC**
  - **Low-FSC:** $FSC < 0.3$,
  - **Mid-FSC:** $0.3 \leq FSC \leq 0.7$,
  - **High-FSC:** $FSC > 0.7$.

- **MARS FSC**
  - **Low-FSC:** $FSC < 0.3$,
  - **Mid-FSC:** $0.3 \leq FSC \leq 0.7$,
  - **High-FSC:** $FSC > 0.7$.

- **MOD10 FSC**
  - **Low-FSC:** $FSC < 0.3$,
  - **Mid-FSC:** $0.3 \leq FSC \leq 0.7$,
  - **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 backward 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...