Using time series to improve endmembers estimation on multispectral images for snow monitoring

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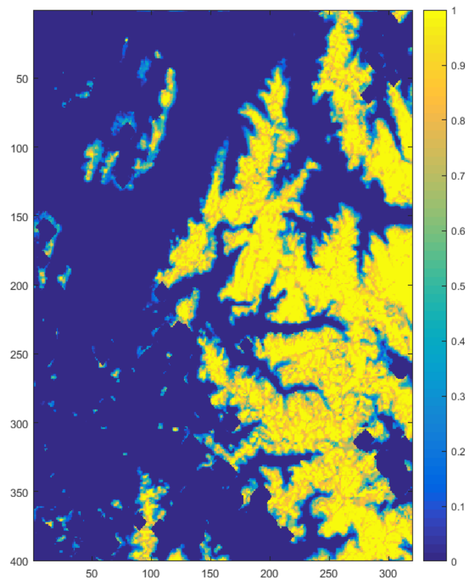
Context

Snow cover monitoring using MODIS images

- Low spatial resolution (250-500 m)

- High revisit time (1 day)

- Acquisitions in the visible and NIR domains



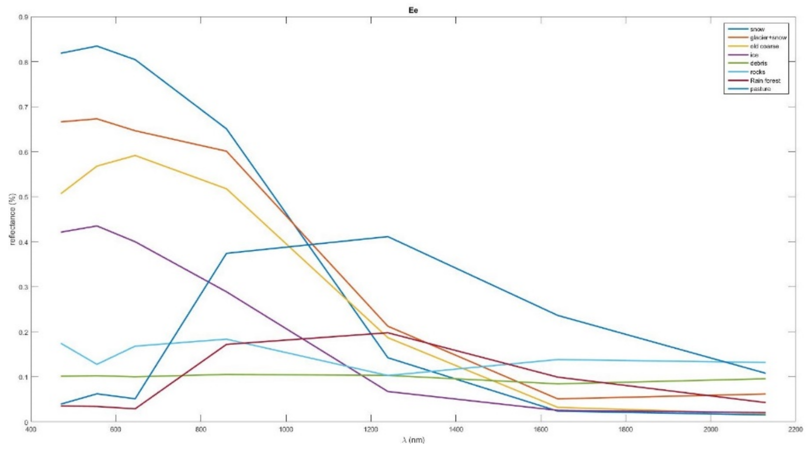
Snow cover maps based on Spectral Unmixing

-> based on a library of endmembers (Painter & al, 2010 Sirguey & al, 2009)

-> Application driven

-> based on estimations done on images

-> More representative but less interpretable



Spectral Unmixing

Considering $\boldsymbol{E} = [\boldsymbol{e}_1, \dots, \boldsymbol{e}_m]$, $\boldsymbol{e}_i \in \mathbb{R}^q$ the spectral signature of endmembers in q spectral bands

The Linear Mixing Model of the spectrum $\boldsymbol{r}$ of pixel p:

$$\boldsymbol{r}_p = \sum_{i=1}^{m} \boldsymbol{e}_i \phi_{i,p} + \boldsymbol{n}_p$$

Where $\boldsymbol{\phi}_p = [\phi_{1_p}, \dots, \phi_{m_p}]$ are fractional per pixel abundances and $\boldsymbol{n}$ is noise

$$\hat{\phi}_p = \arg\min_{\phi_p} \left\| \boldsymbol{r}_p - \sum_{i=1}^{m} \boldsymbol{e}_i \phi_{i,p} \right\|_2$$

Spectral Unmixing

- With Abundance Non-negative ($\phi_i \geq 0$) and Sum-to-one ($\sum_{i=1}^{m} \phi_i = 1$) Constrain (resp. ANC and ASC)

  -> Full Constrained Least Square Unmixing (FCLSU)

- With parcimonie :

$$\hat{\phi}_p = \arg\min_{\phi_p} \frac{1}{2} \left\| \boldsymbol{r}_p - \sum_{i=1}^{m} \boldsymbol{e}_i \phi_{i,p} \right\|_2^2 + \lambda \left\| \phi_p \right\|_1$$

Example : SUnSAL (Bioucas-Dias and Figueiredo, 2010)

- Spectral variability :

$$\hat{\phi}_p = \arg\min_{\phi_p} \left\| \boldsymbol{r}_p - \sum_{i=1}^{m} \phi_{i,p} \, f_{i,p}(\boldsymbol{e}_i) \right\|_2$$

Example : ELMM (Drumetz & al., 2015)

where $f_{i,p} = \Psi_{i,p} \boldsymbol{e}_{0,i}$ and Ψ is a matrix gathering all the scaling factors for all P pixels

Spectral unmixing approaches

Endmembers estimation

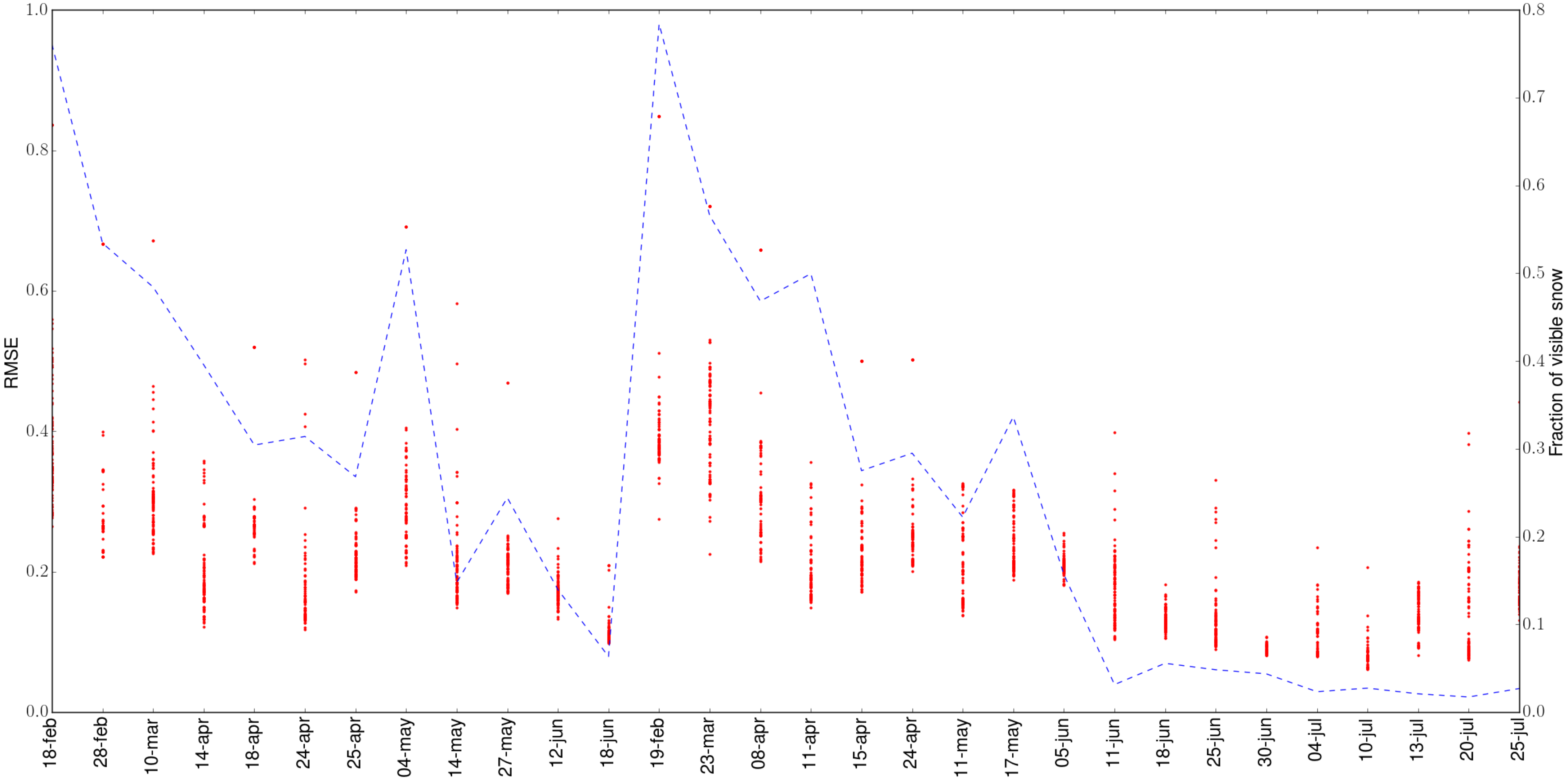
- Geometrical approaches (e.g.,Vertex Component Analysis (VCA)) Nascimento, J. and Bioucas Dias, J., 2005.
- Minimum volume approaches (e.g.,Simplex identification via split augmented Lagrangian (SISAL), J. M. Bioucas-Dias, 2009

Abundances estimation

- FCLSU
- Sparsity (e.g., SUnSAL) Bioucas-Dias and Figueiredo, 2010
- Spatial regularization (e.g., SUnSAL_vtv)
- Spectral variability (e.g., ELMM (Drumetz & al., 2015)

- Clusters (e.g.,AEB Somers & al., 2012 ,FDN Jin & al., 2010)

Daily estimation



Issue : mixed pixels and spectral variability

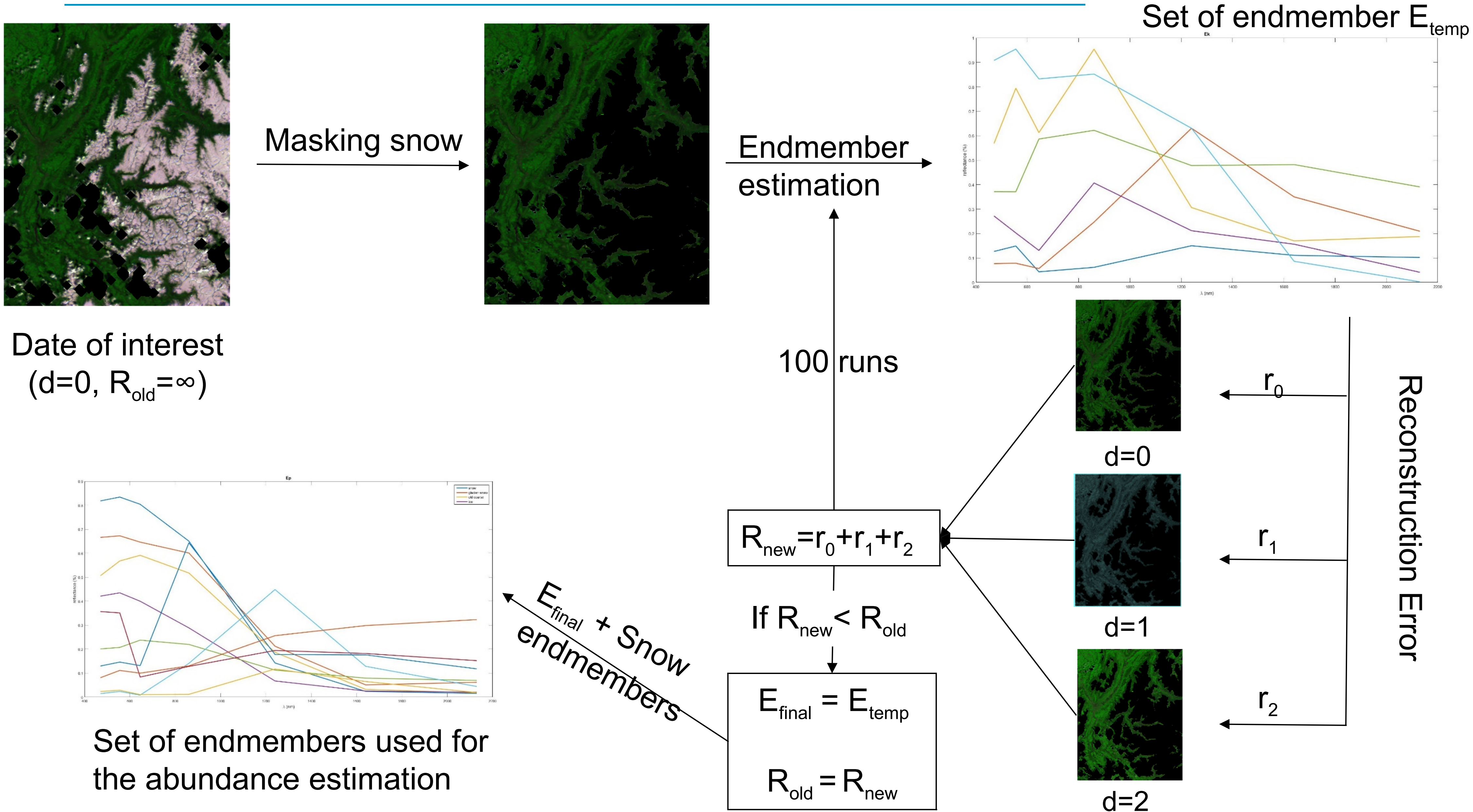
Usual approaches

Endmembers estimation	Abundances estimation
Vertex Component Analysis (VCA)	FCLSU
Geometric	SUnSAL
Cluster (AEB, FDN)	SUnSAL_vtv
	ELMM

Designed for spectral variability

Issue : mixed pixels / time

Proposed approach



Experimentation :

<u>Endmember estimation</u>

- VCA (1 date over all pixels)
- VCA (1 date over non-snow pixels)
- VCA with 3 dates

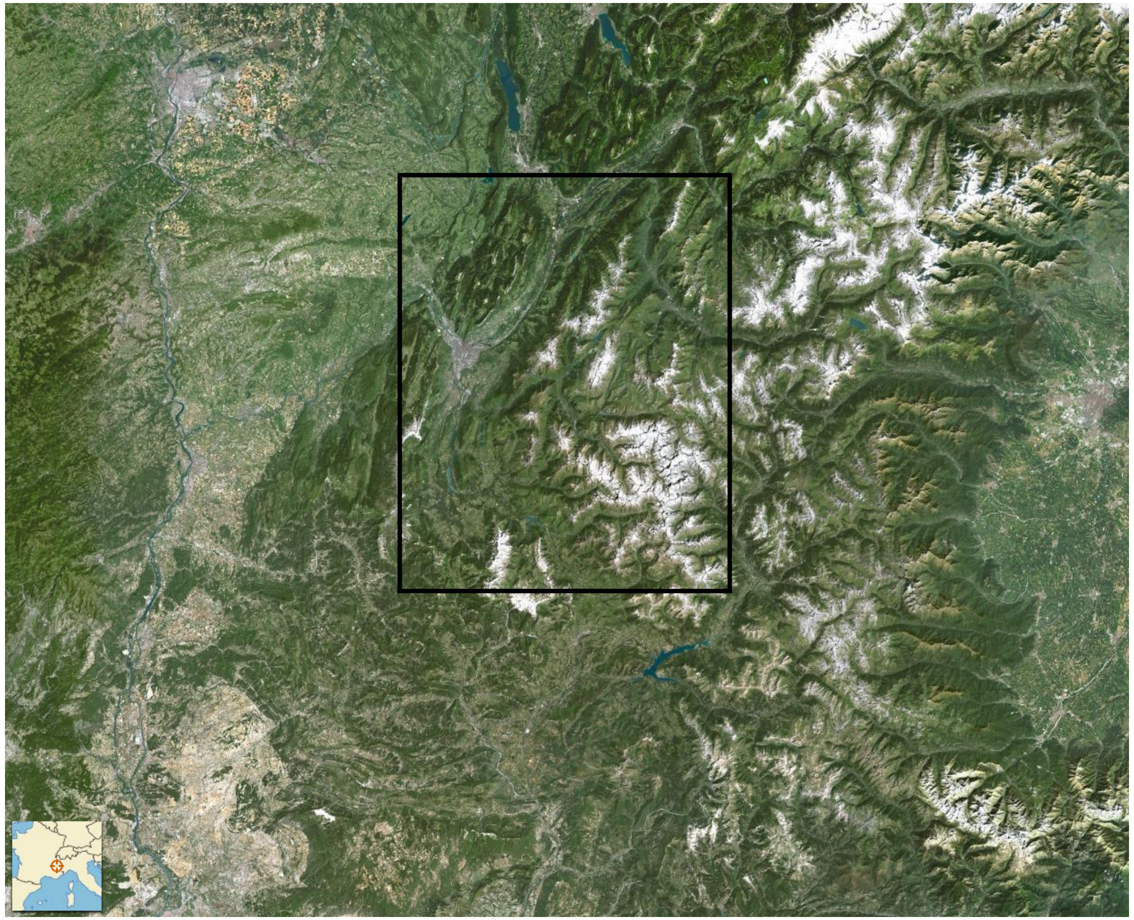
Our approach

<u>Abundance estimation</u>

- FCLSU
- SUnSAL
- SUnSAL_vtv
- ELMM

- Cluster (AEB, FDN)

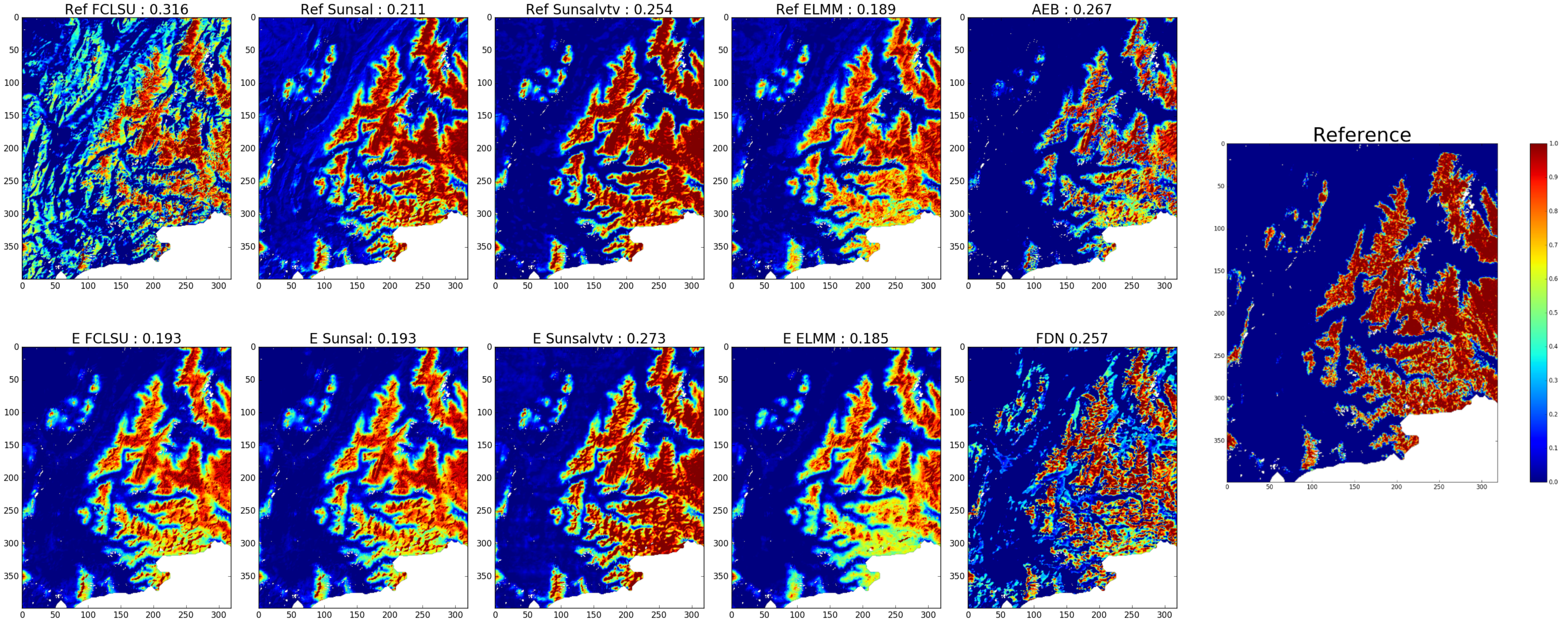
Tested area : The Alps near Grenoble



30 dates, 320x400 pixels

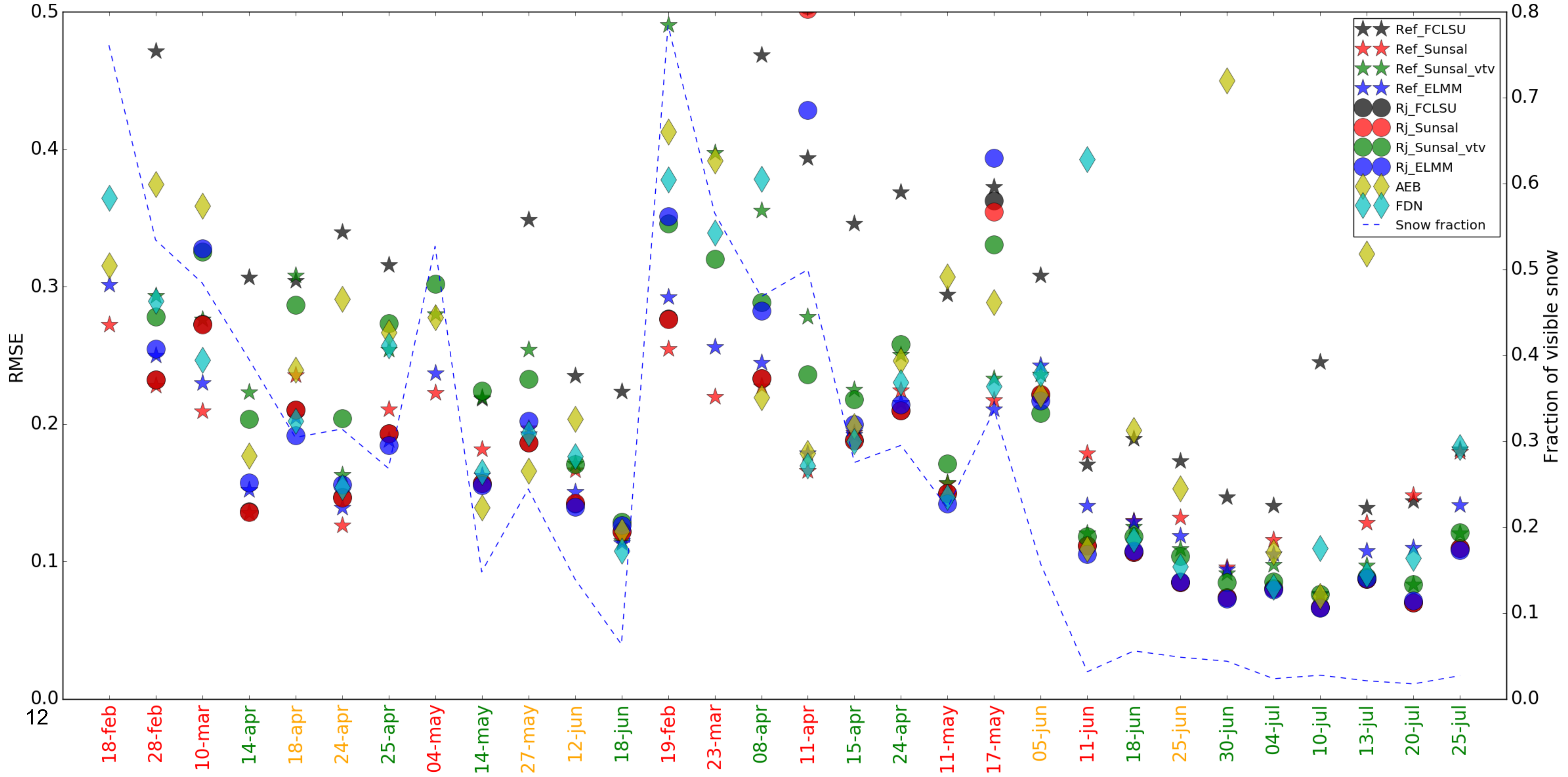
set up:
- 3 consecutive dates
- 100 test for reconstruction error
- 15 dates considered

Results : visual interpretation

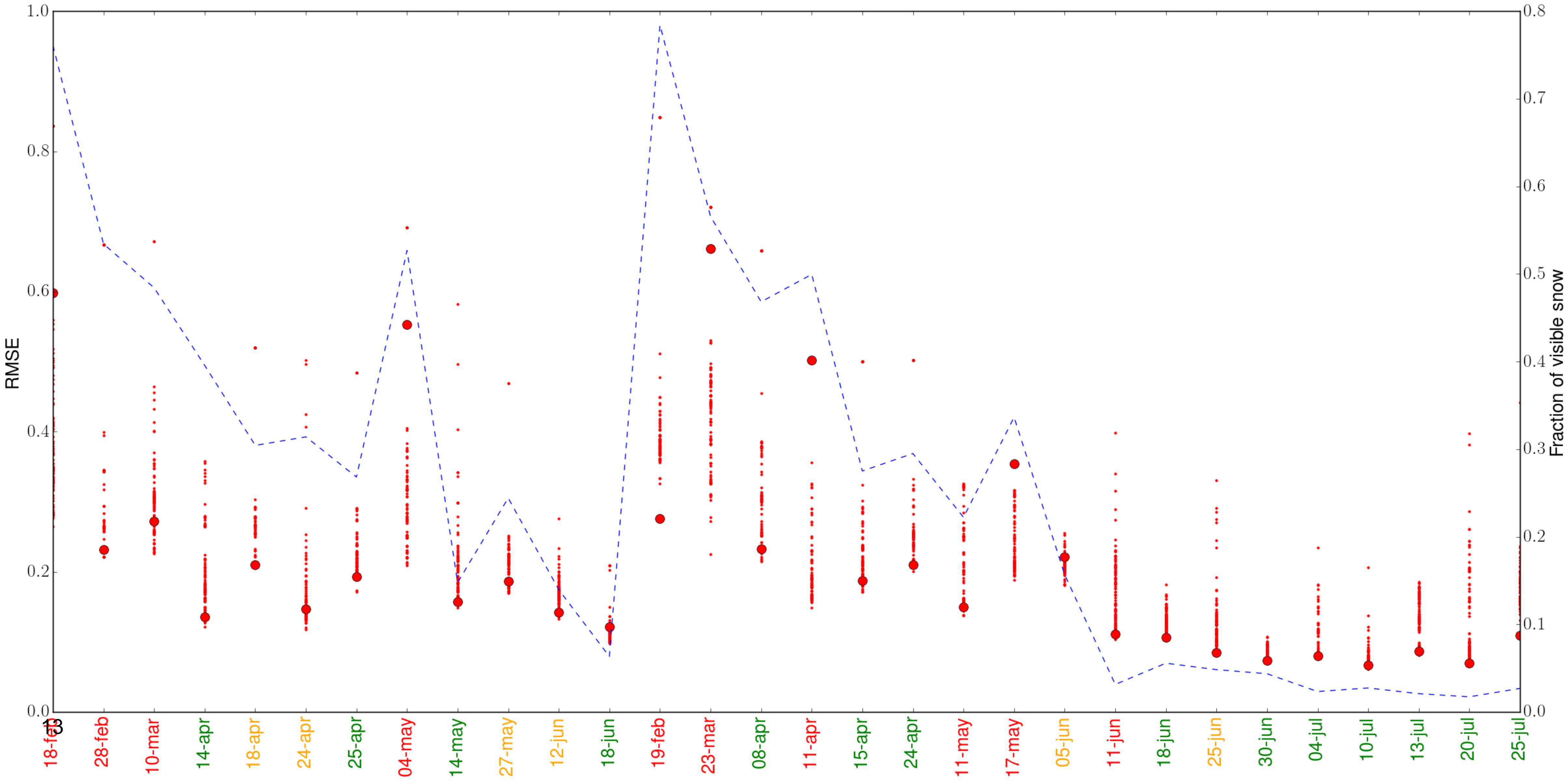


Results : quantitative results

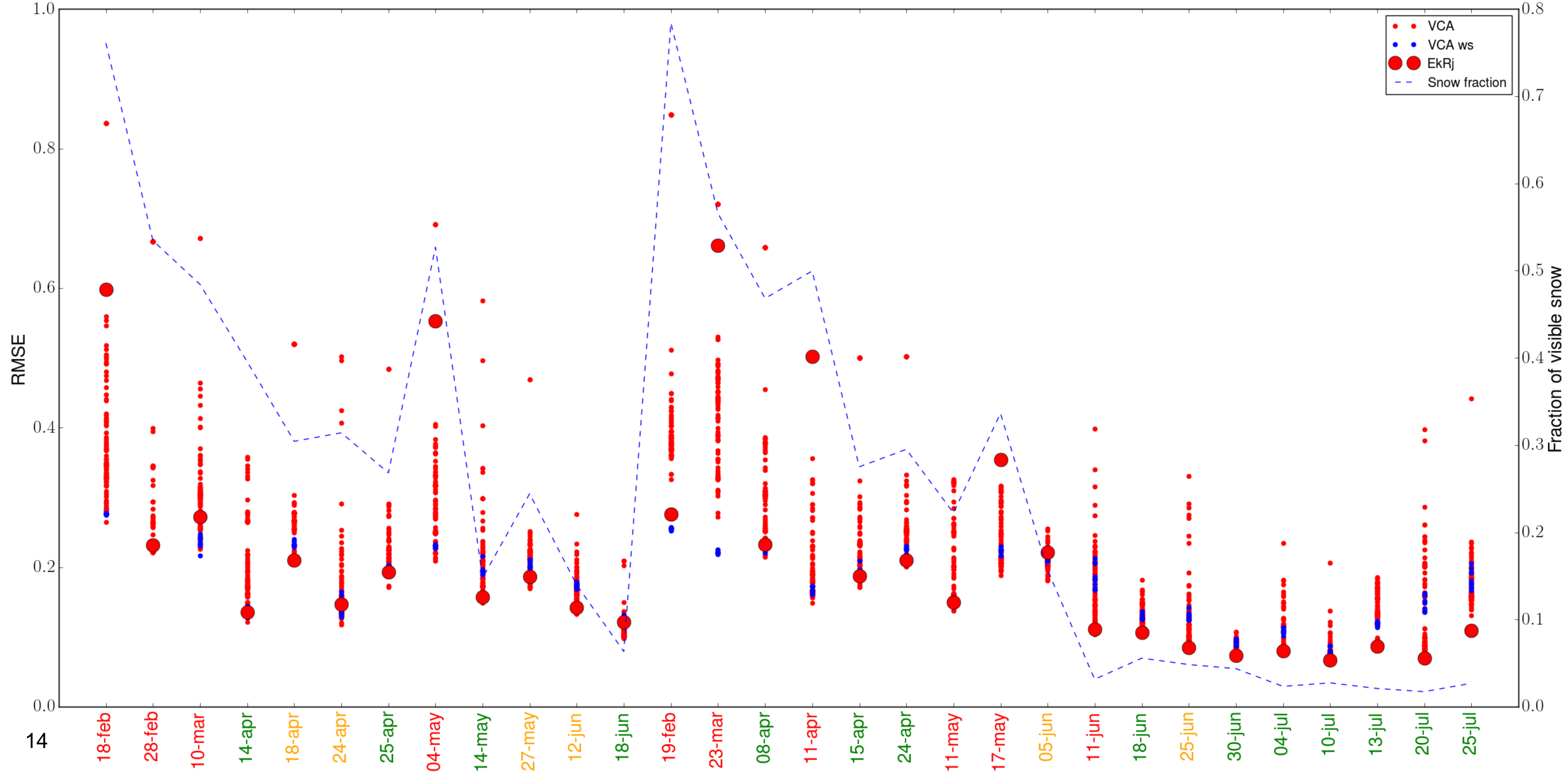
Red : 1 date
Orange : 2 dates
Green : 3 dates



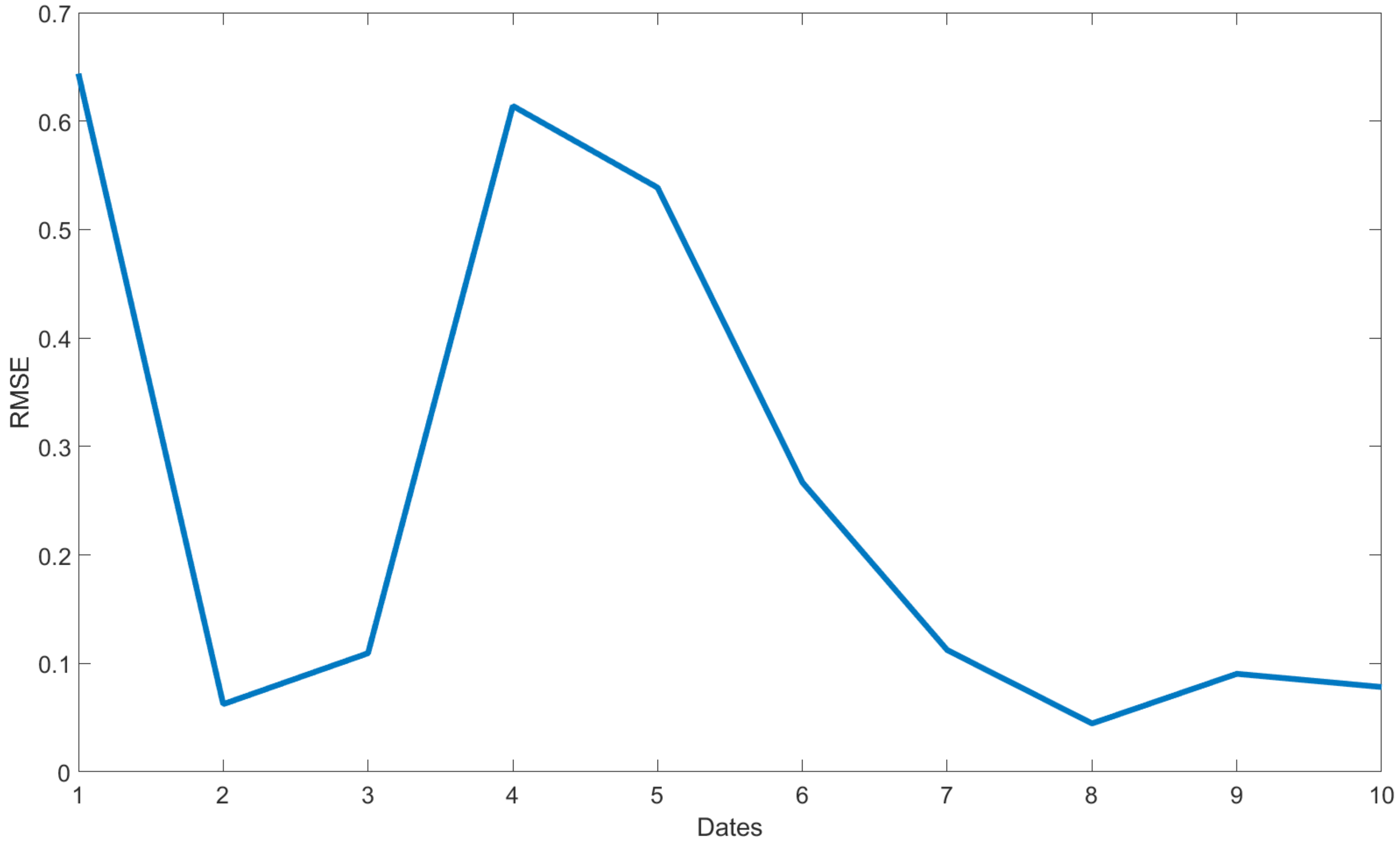
Results: comparison with daily endmembers estimation



Results: comparison on areas without snow



Effect of the number of dates



Conclusions and perspectives

- Large improvement between SU performed daily
  - Easy to implement, stability of the result
  - Limitation: need for consecutive cloud free acquisitions

- Spectral unmixing :
  - Large differences between FCLSU and SUnSAL in case of misfit set
  - Spatial regularisation not fully appropriate for snow cover monitoring
  - ELMM high performance in most of the cases (but time consuming)

- Applications/perspectives:
  - High return time but low spatial and spectral resolution → consider images from different sensors
  - Generalize the proposed spectral unmixing scheme