4TH WORKSHOP – REMOTE SENSING AND MODELING OF SURFACES PROPERTIES

Towards the assimilation of MODIS reflectances into the detailled snowpack model SURFEX/ISBA- Crocus

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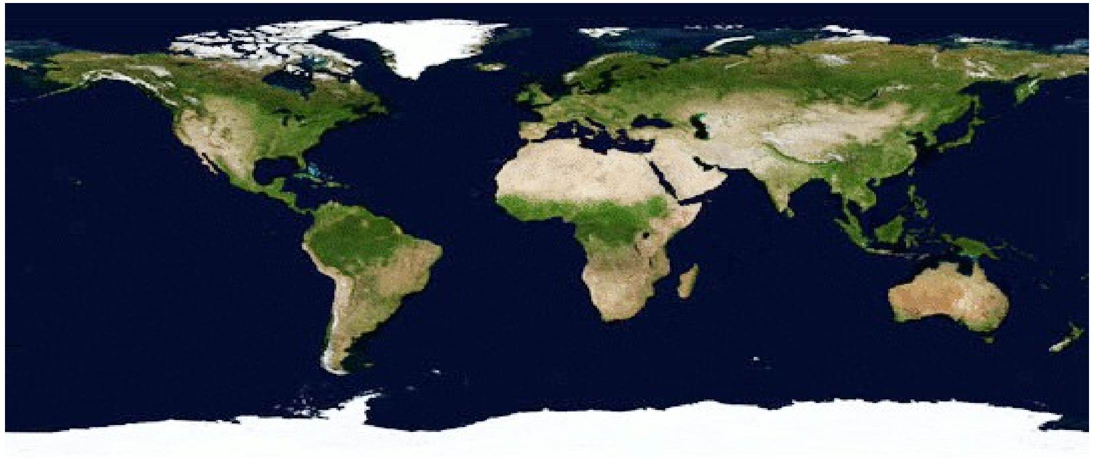
Snow cover

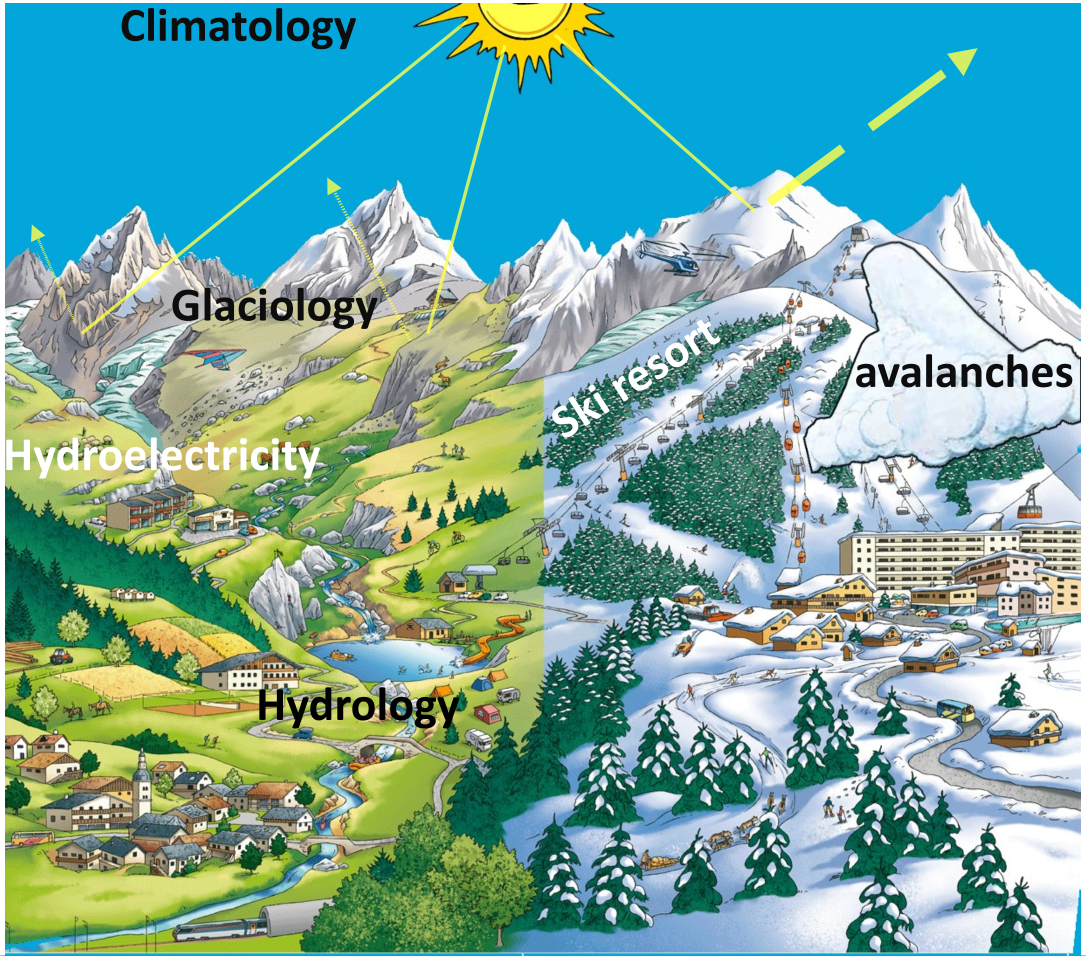
Large scale



- **<u>Seasonal snow cover:</u>**
  - Surface North hemisphere ~ **100 x10^6 km^2**
  - Snow cover up to ~ **40 - 50 x10^6 km^2 (up to 50% !!)**

- Permanent snow (glacier & icesheet) ~**16 x10^6 km^2**
- Snow on sea ice ~ **24 x10^6 km^2**

Regional scale



Snowpack modeling

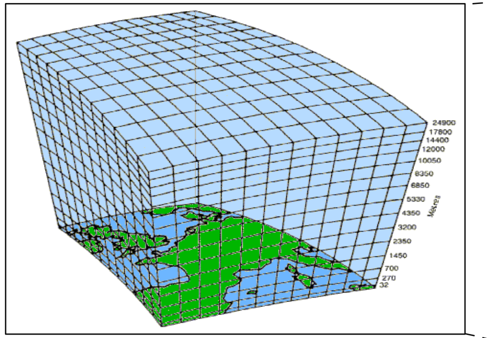
Models chain (SAFRAN- SURFEX/ISBA – Crocus)

SAFRAN

Système d'**A**nalyse **F**ournissant des **R**enseignements **A**tmosphériques à la **N**eige

[Durand et al., 2009]

ATMOSPHERIC MODEL

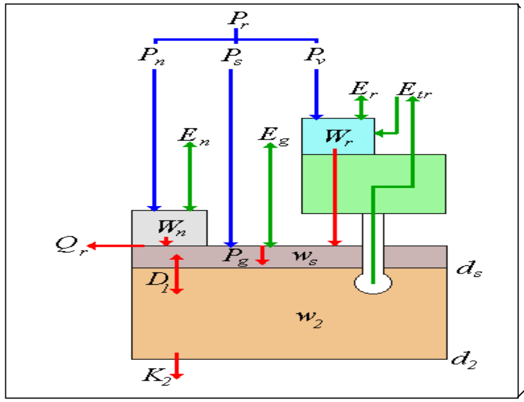


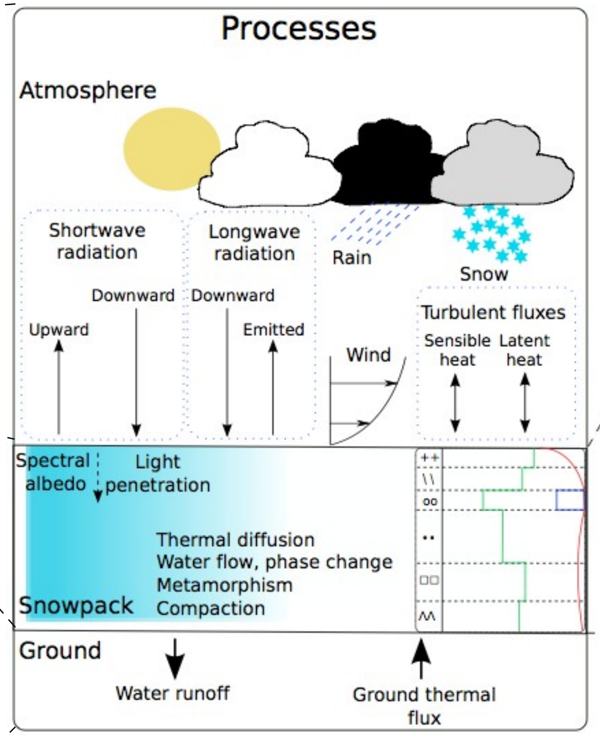
SURFEX/ISBA

Interactions between **S**oil, **B**iosphere and **A**tmosphere

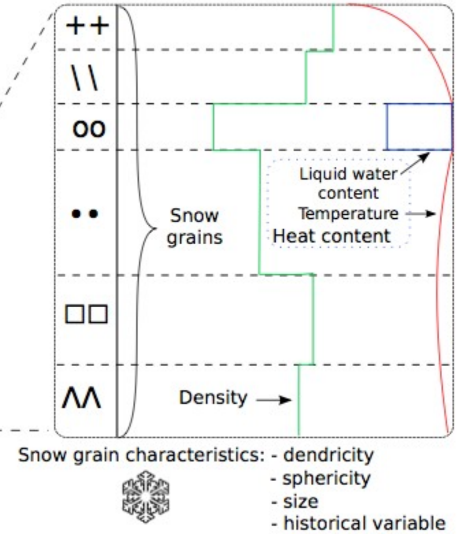
[Masson et al., 2013; Boone and Etchevers, 2001]

LAND SURFACE MODEL

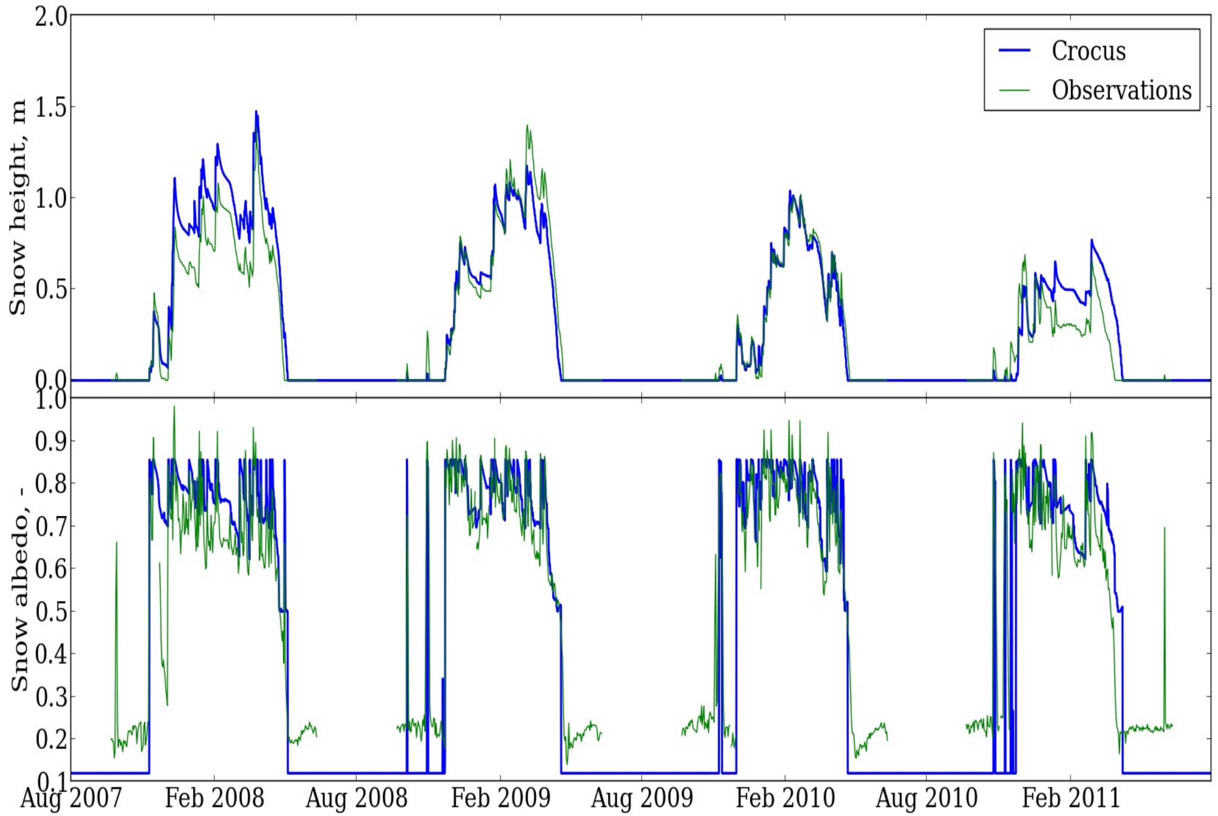




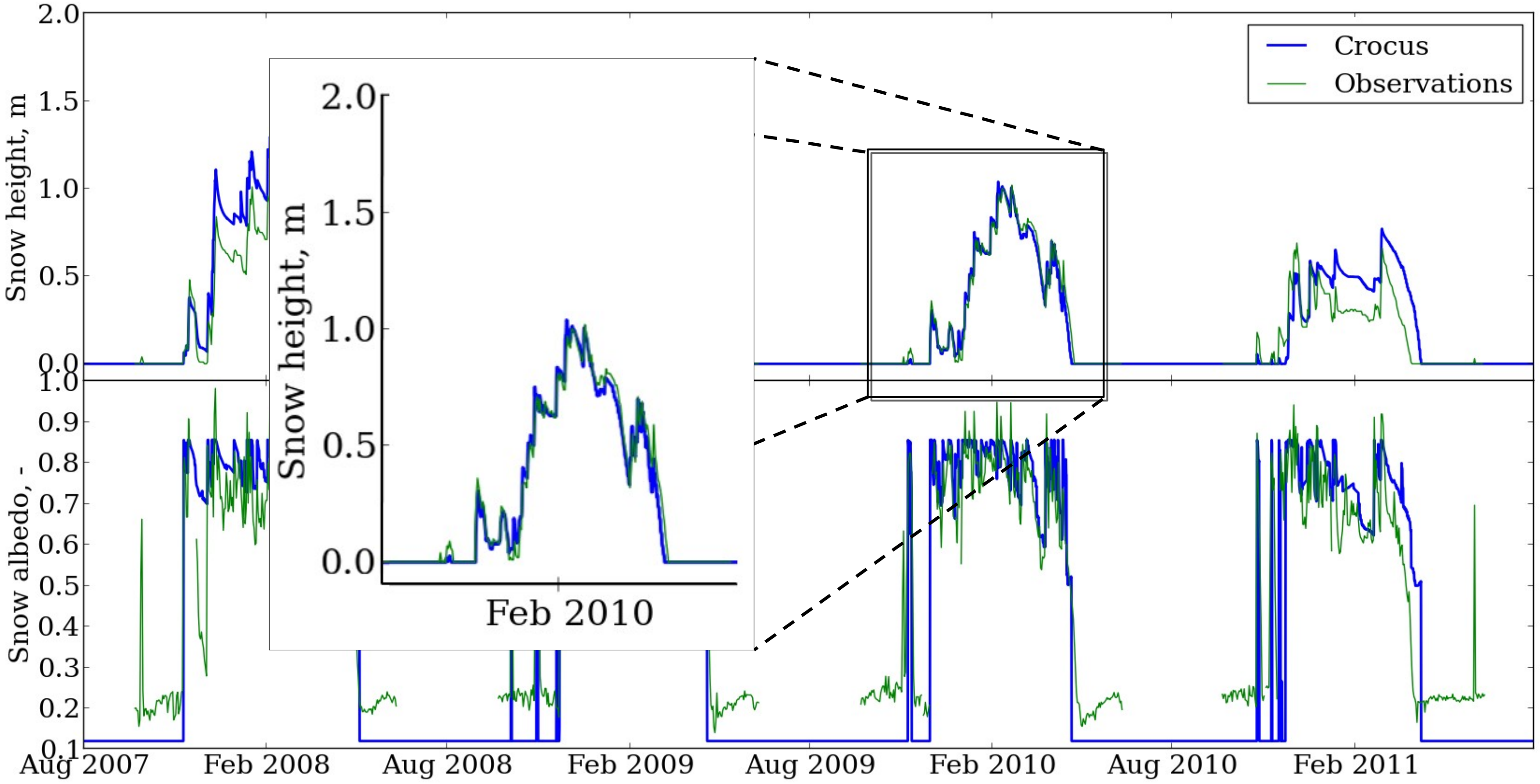
CROCUS MODEL



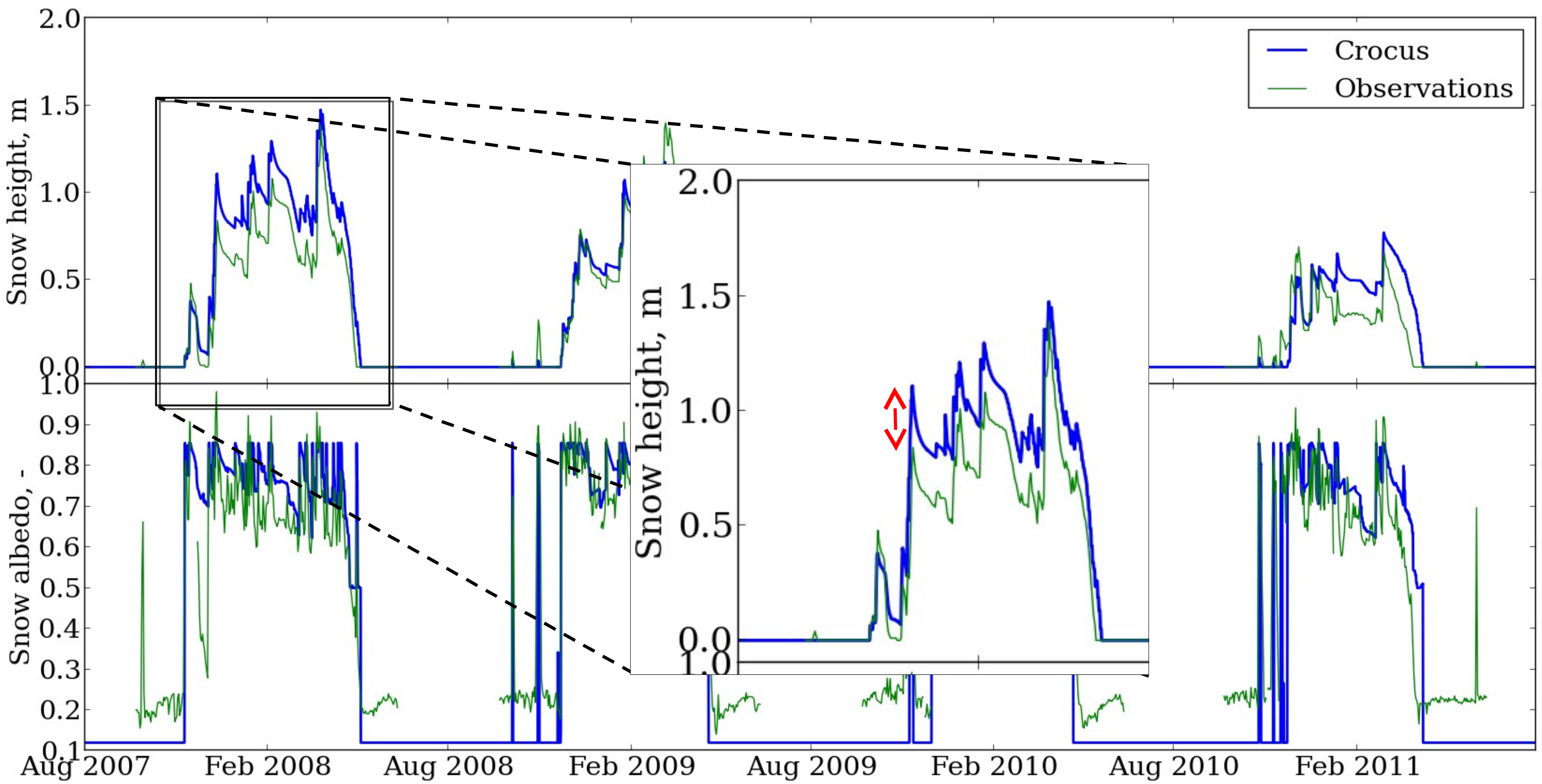
Comparisons at Col de Porte site (1326m)



And that can work well !



But not so easy (real world!) ...



Simulation uncertainties

If error during simulation, error propagates over time !

Main error sources come from **the meteorological forcings** [Raleigh et al., 2015]

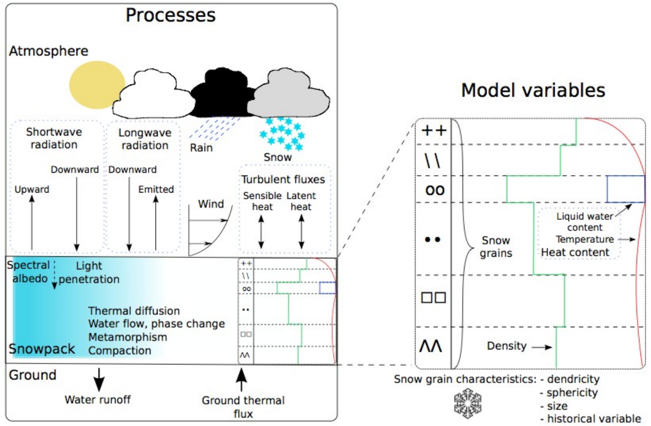
What solutions?

Data Assimilation: Ingredients !

Combine different sources of information to estimate at best the state of a system.

Model

- SURFEX/ISBA - Crocus



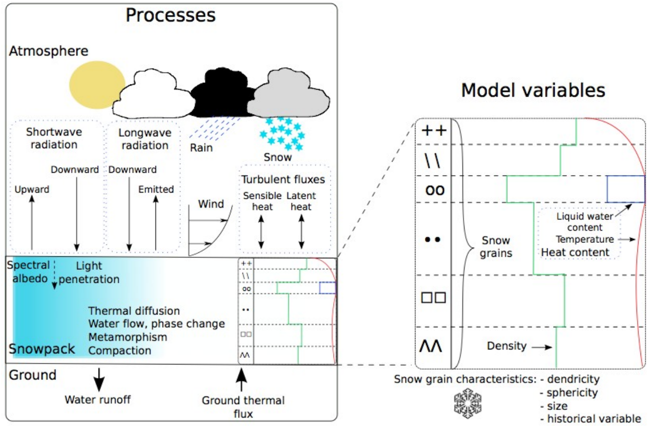
- non-linear
- Crocus uncertainties ascribed to meteorological forcing
- Dynamic vertical discretisation

Data Assimilation: Ingredients !

Combine different sources of information to estimate at best the state of a system.

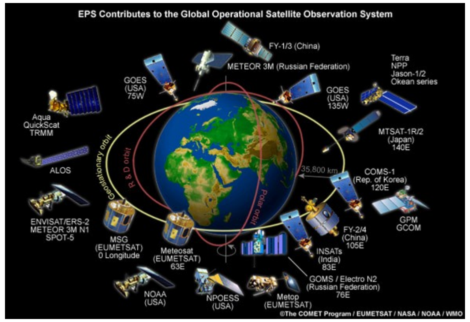
Model

- SURFEX/ISBA - Crocus



- non-linear
- Crocus uncertainties ascribed to meteorological forcing
- Dynamic vertical discretisation

Observations



Satellites observations

Ground automatic measurements

In situ measurements

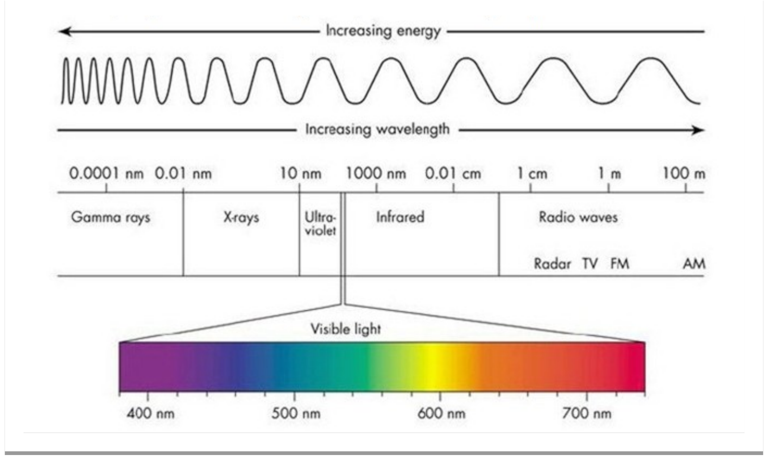
Satellite observations

Microwave data

+
- Cloud coverage
- Penetrate down snowpack

−
- Coarser resolution (passive)
- Wet snow (passive/active)
- Lack of data (active)

[Andreadis et Lettenmaier, 2005; Che et al., 2014; Liu et al., 2013; De Lannoy et al., 2012; Phan et al., 2013; Dechant et al., 2012; ….]



Optical data

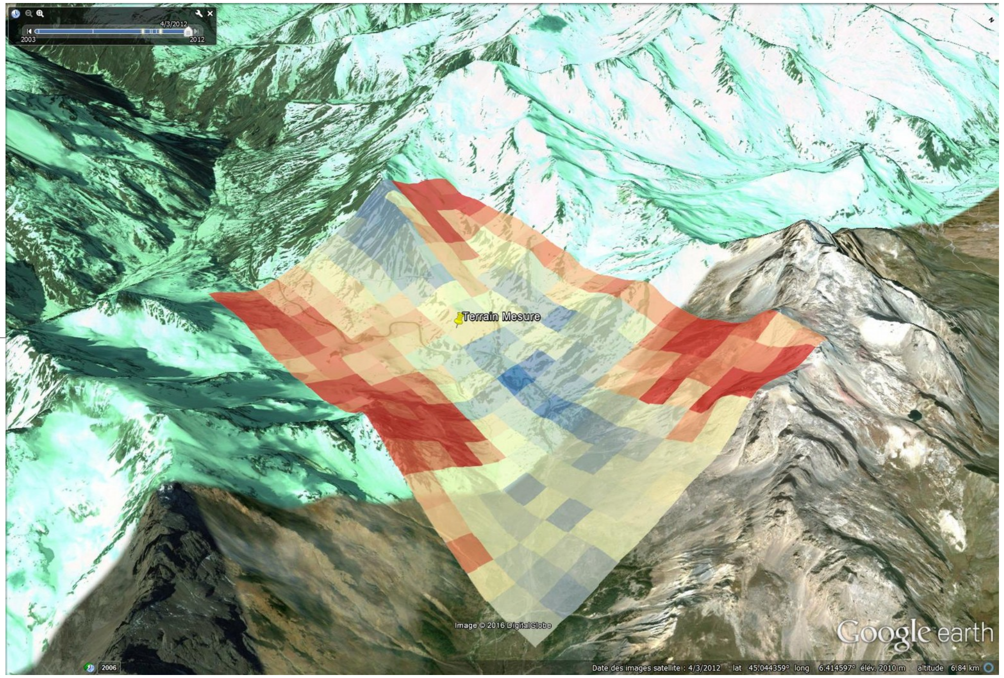
−
- Surface information
- Cloud coverage
- Canopy

+
- Snow products: SCF, Albedo, grain size
- Next slide ..

SCF AD: [Andreadis et Lettenmaier, 2005; De Lannoy et al., 2012; …]

Albedo AD: [Dumont et al., 2012]

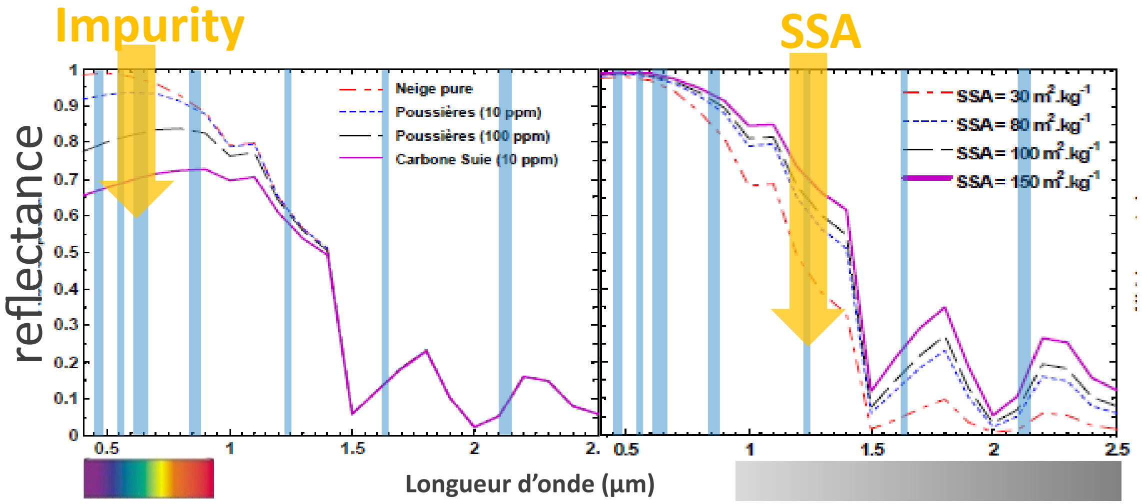
MODIS
MODerate resolution Imaging Spectradiometer



MODimLab: MODIS Algorithm (Atmospheric, topographic, anisotropy..)

[Sirguey et al., 2009]

- Sensitivity to snowpack properties
  Impurity content & SSA
- Spatial & temporal resolution
  250x250m / 1 overpass / day
- 7 spectral bands



- **Observation operator**

[Libois et al., 2013, 2014]: implemented into Crocus, a new radiative model **TARTES** provides **spectral reflectances** matching MODIS data

Data Assimilation: Ingredients !

Combine different sources of information to estimate at best the state of a system.

Model → **Observation operator**

- SURFEX/ISBA – Crocus
  though TARTES model
  - No-linear model
  - Crocus uncertainties ascribed to meteorological forcing
  - Dynamic vertical discretization

Observations

- MODIS Reflectances data (Visible-IR, 7 bands) **[Sirguey et al., 2009]**
  - First attempted
  - Radiance data
  - Observations sensible to:
    - Cloud coverage / atmosphere
    - First mm or cm to snowpack

Data Assimilation

Data Assimilation, which one?

Combine different sources of information to estimate at best the state of a system.

Data Assimilation
LGGE - MEOM

- Kalman Filter

  [Liu et al., 2013, De Lannoy et al., 2012; Slater and Clark, 2005; Chet et al., 2014; Andreadis and lettenmaier, 2005, Abaza et al., 2015; …]

- Variational methods

  [Dumont et al., 2012, Phan et al., 2014, …]

- Particle Filter

  [Dechant et al., 2010; Leisenrig and Moradkhani, 2010, …]

Depends on …

- Uncertainty estimation
- Linear / Non Linear Model
- Gaussian error distribution
- Computation time
- Model structure
- …

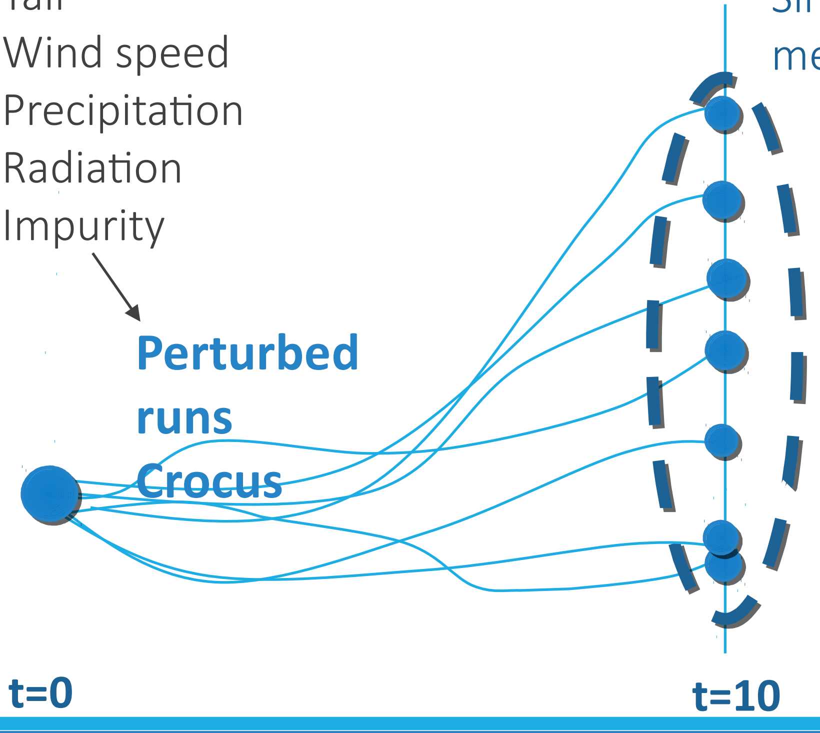
Ensemble method

Combine different sources of information to estimate at best the state of a system.

Ensemble of meteorological forcing:

Tair
Wind speed
Precipitation
Radiation
Impurity

Simulation uncertainty from meteorological uncertainty



In our case

Main error sources come from **the meteorological forcings** [Raleigh et al., 2015]

- Uncertainty quantification

Ensemble methods

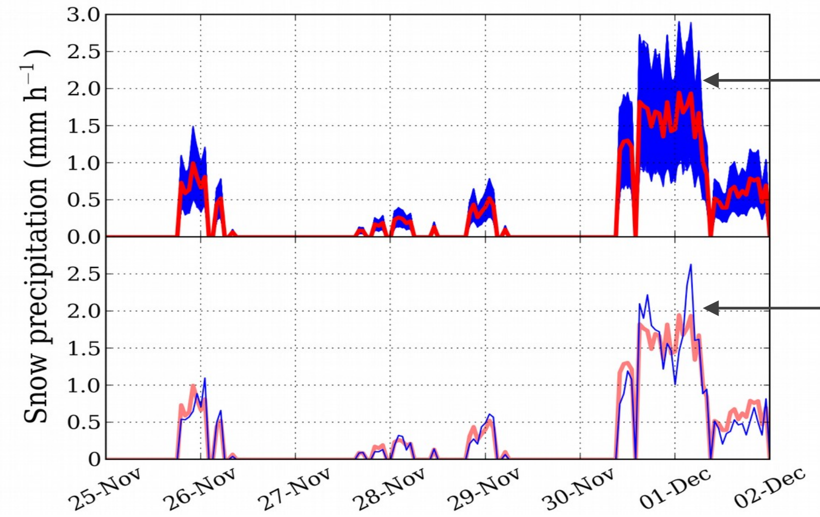
Generation of an ensemble of perturbed meteorological forcings

Comparisons between in situ measurements and SAFRAN estimations (18 years)

- Tair
- Wind speed
- Precipitations
- Radiations (SW/LW)

Uncertainty of all variables forcing

Stochastic Perturbation method
AutoRegressive Model AR(1)
Based on Col de Porte statistics
Introduction of perturbation at each time step



Ensemble of perturbed forcing (300 members)

1 perturbed forcing

Data assimilation, which one?

Combine different sources of information to estimate at best the state of a system.

Data Assimilation
LGGE - MEOM

- **Kalman Filter**

  [Liu et al., 2013, De Lannoy et al., 2012; Slater and Clark, 2005; Chet et al., 2014; Andreadis and lettenmaier, 2005, Abaza et al., 2015; …]

- **Variational methods**

  [Dumont et al., 2012, Phan et al., 2014]

- **Particle Filter** [Van Leeuwen, 2009, 2014]

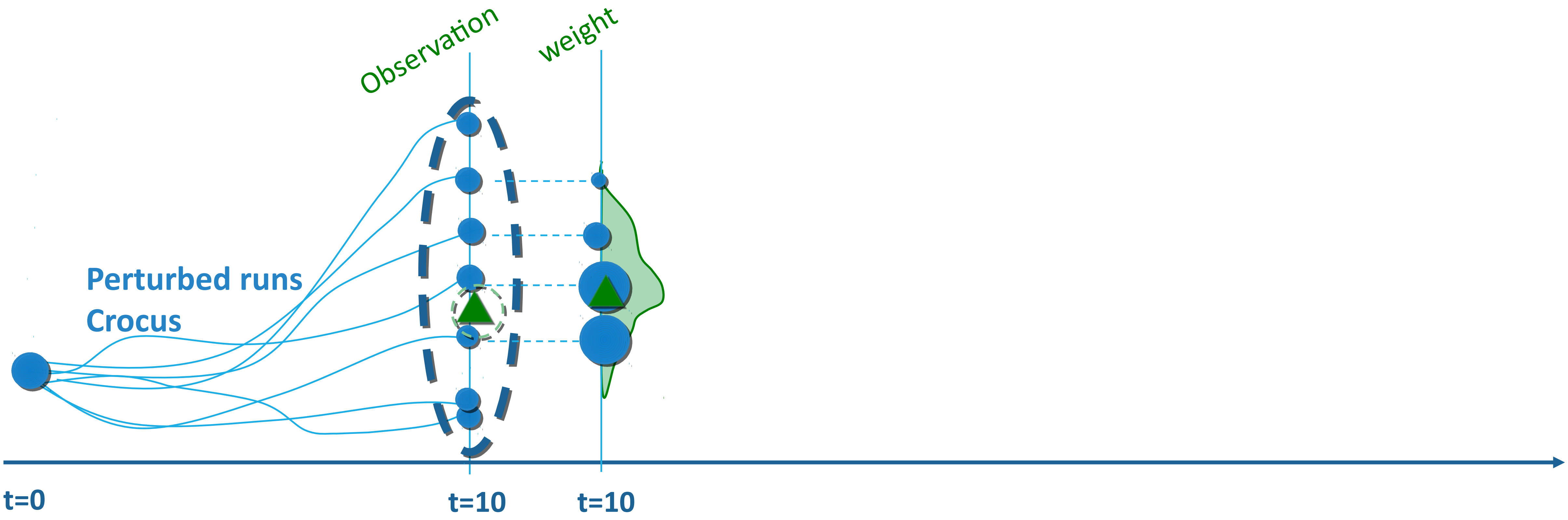
In our case

- Uncertainty quantification
- Non Linear Model
- Dynamical Layering
- Easy to implement
- No concerned on computation time (for now)

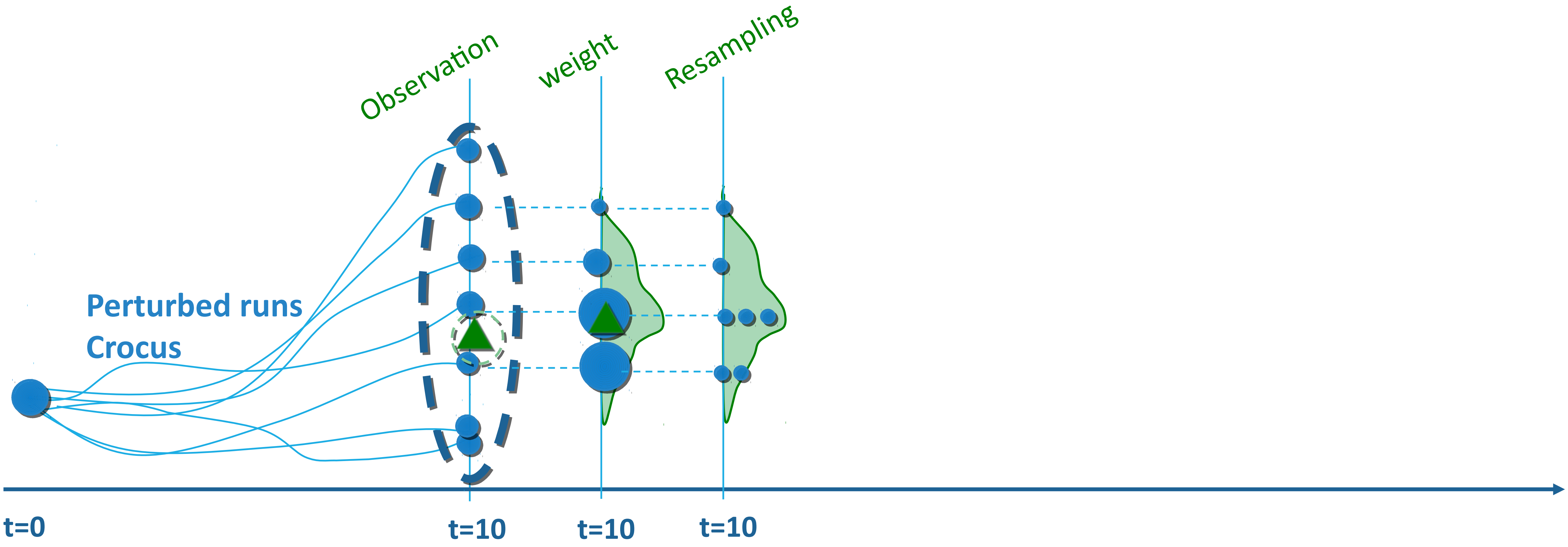
Particle Filter
Sequential Importance Resampling

Stochastic meteorological forcing:
Tair
Wind speed
Precipitation
Radiation
Impurity

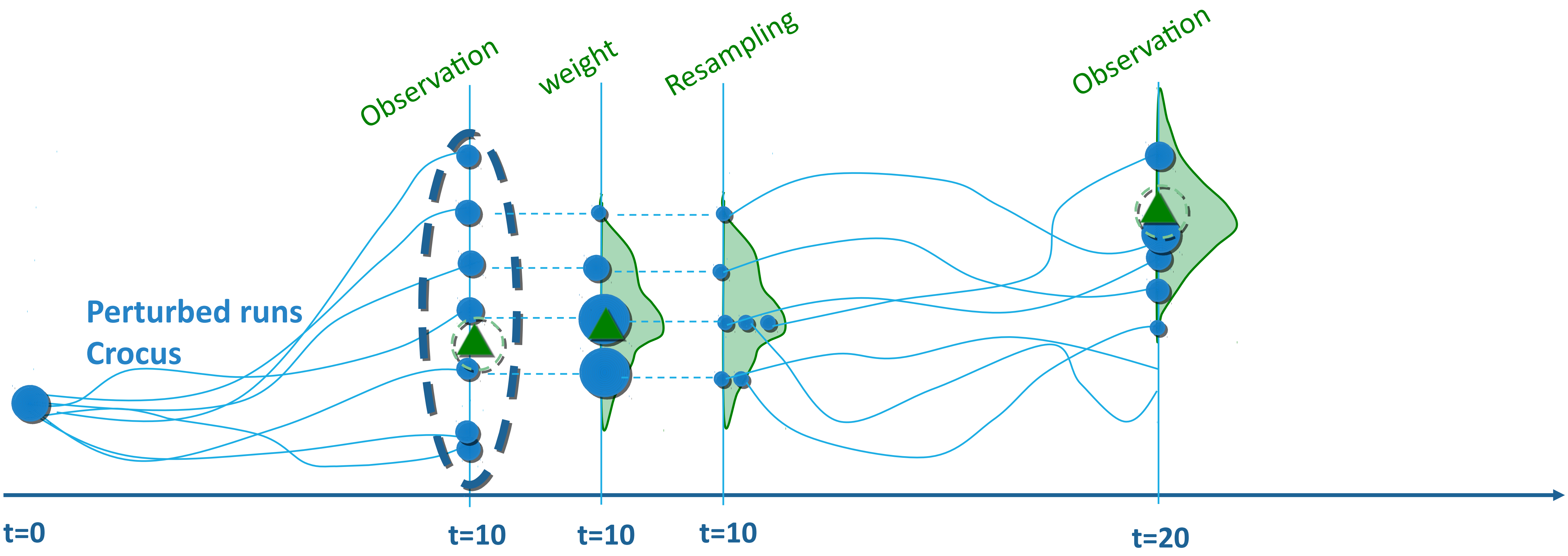
Particle Filter
Sequential Importance Resampling



Particle Filter
Sequential Importance Resampling



Particle Filter
Sequential Importance Resampling



Data assimilation into Crocus
Many challenges …

Model → **Observation operator**

- SURFEX/ISBA – Crocus though TARTES model

Météo-France - CEN

Observations

- MODIS Reflectances data
  Visible-IR, 7 spectral bands

[Sirguey et al., 2009]

Data Assimilation
Particle Filter + SIR
LGGE - MEOM

Forecast

Data assimilation into Crocus
Many challenges …

Model → Observation operator

Observations

- SURFEX/ISBA – Crocus though TARTES model

Météo-France - CEN

- MODIS Reflectances data (Visible-IR) **[Sirguey et al., 2009]**

Twin experiments

synthetic observations to evaluate the feasibility of the data assimilation framework

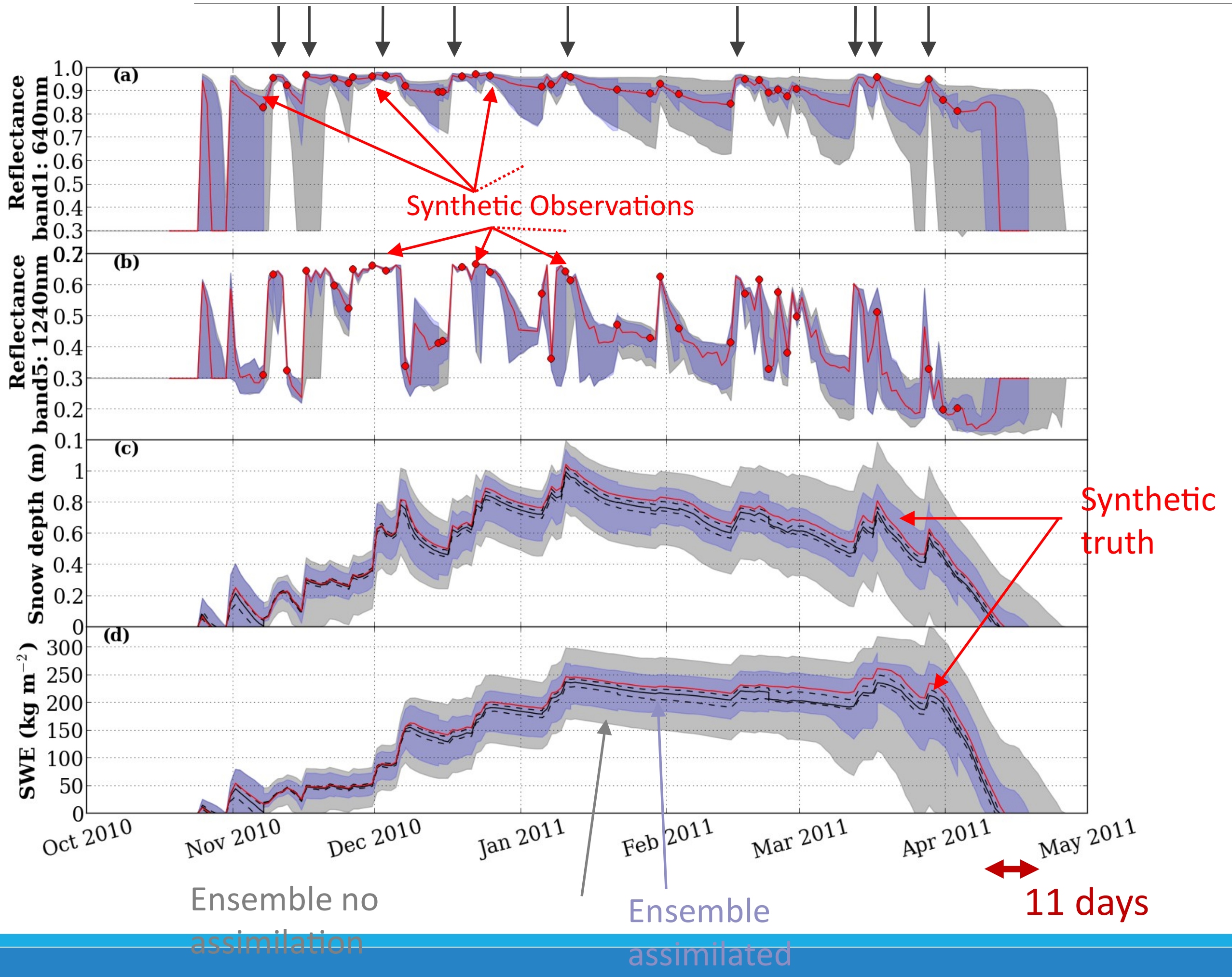
Particle Filter + SIR

LGGE - MEOM

Forecast

Assimilation of reflectances (synthetic observations)

Baseline experiment



RMSE reduction by a factor of 2 compared to ensemble without assimilation

Results

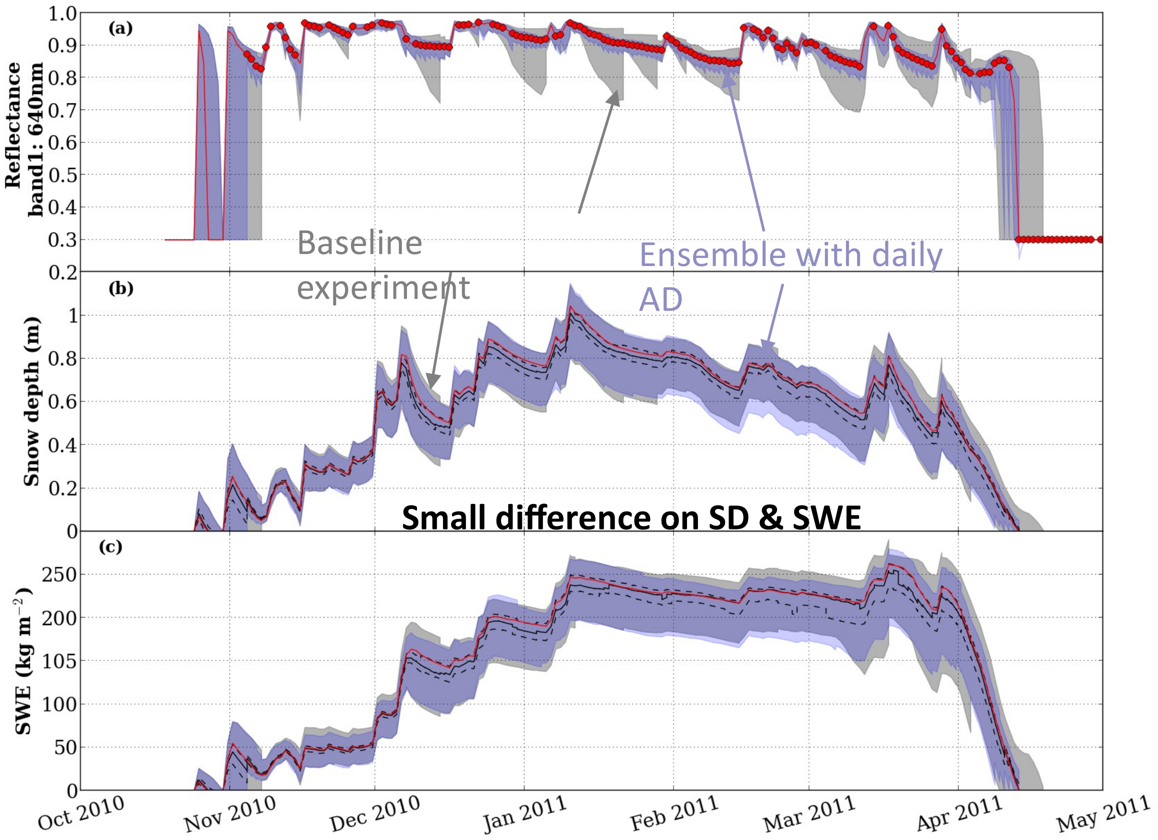
- The RMSE after DA is always lower than prior DA
- Date of complete snow disappearance, 11 days range against 24n without DA

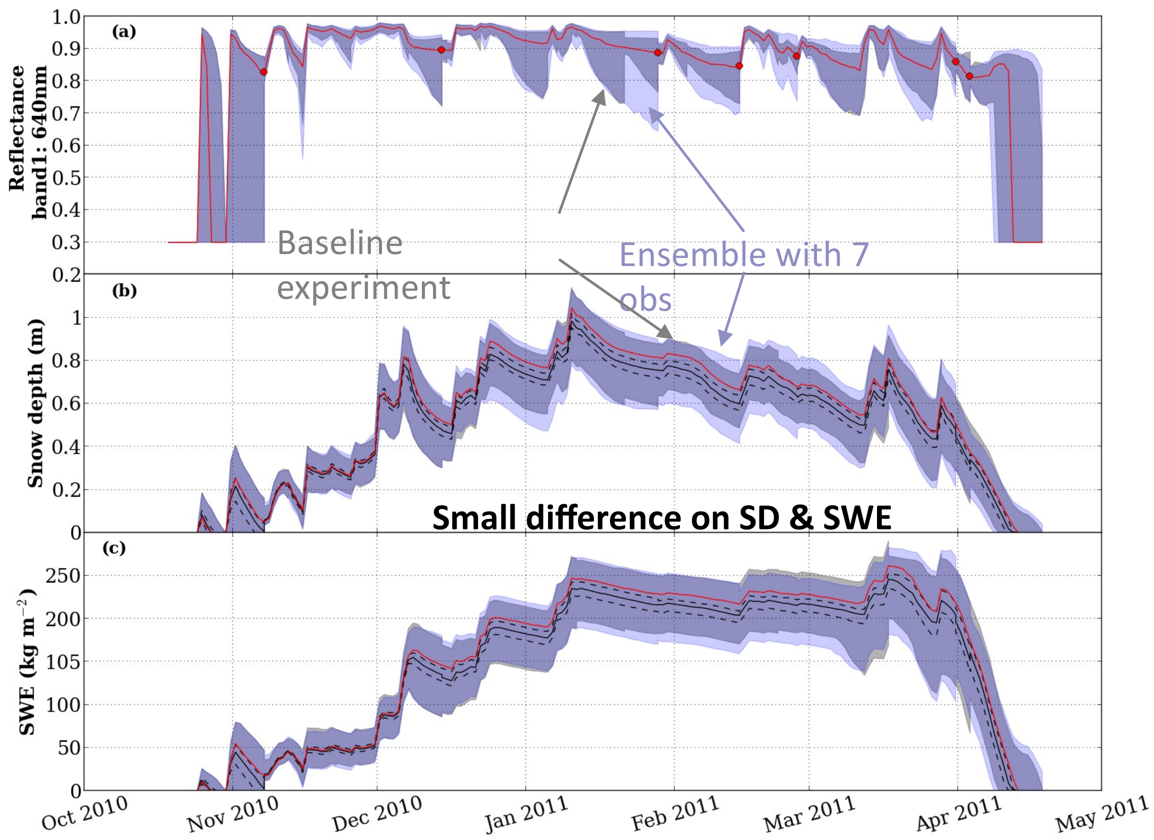
- Resetting process with snow fall events limits SIR efficiency
- Need regular and frequent observations but only 34 dates available over 2010/2011 seasons

Cloud coverage

Daily Assimilation vs Assimilation of 7 observations

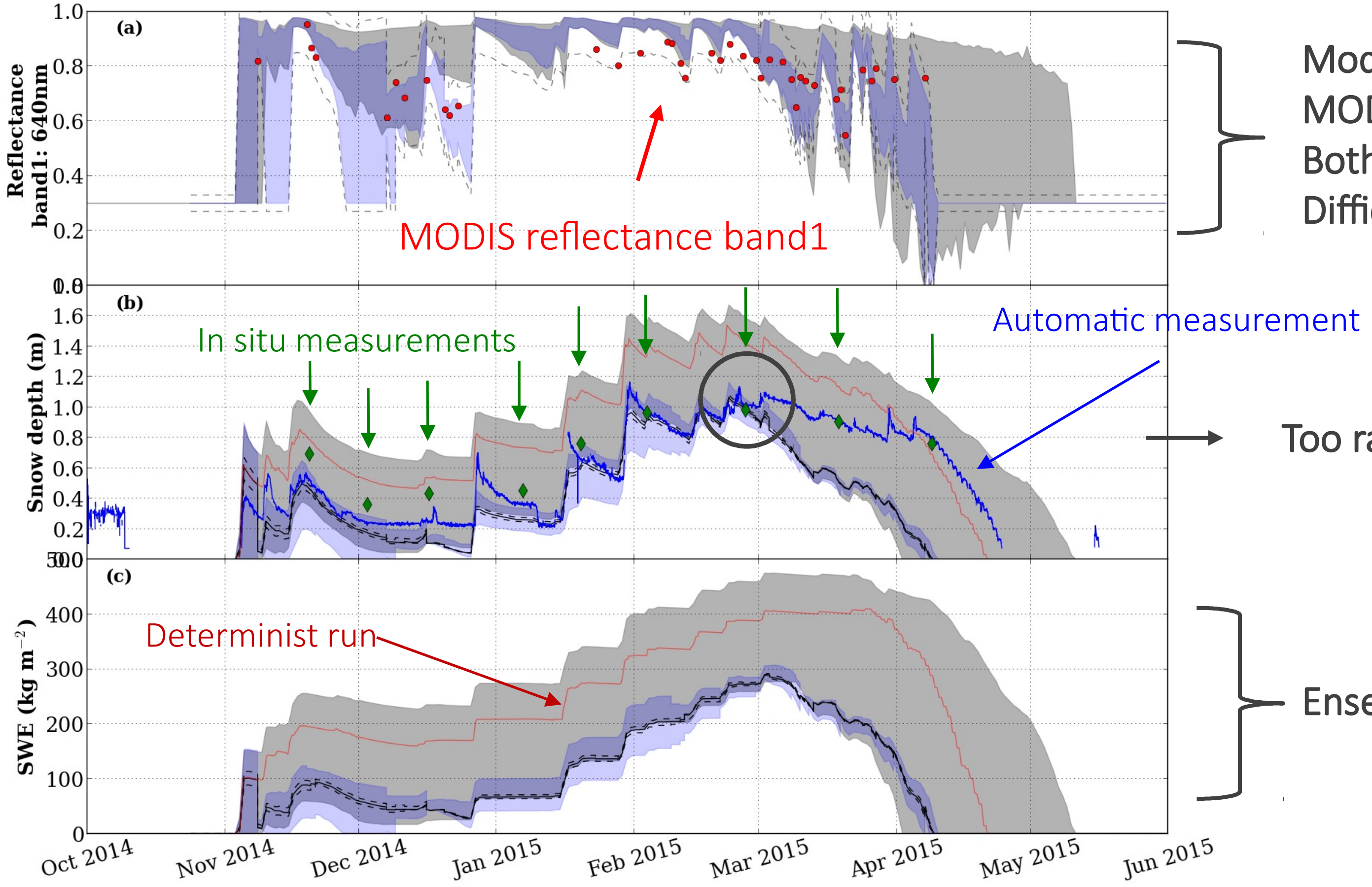
The time distribution of the observation: The end of an extend period without precipitation





Real data

MODIS assimilation, Col du Lautaret 2014-2015



Model overestimates reflectance ?
MODIS algorithm underestimates reflectance ?
Both?
Difficulty for the filter

Too rapid melting in Crocus simulation

Ensemble (no assimilation) under-dispersvive

Conclusion

- Assimilation of synthetic reflectance data
  - High impact in case of thin snow cover
  - RMSE always reduced than prior DA
  - Fresh snow limits the performance of the filter -> need regular observations & well distributed

- Assimilation of synthetic snow depth data
  - Outperforms except for thin snow cover
  - But point-scale information

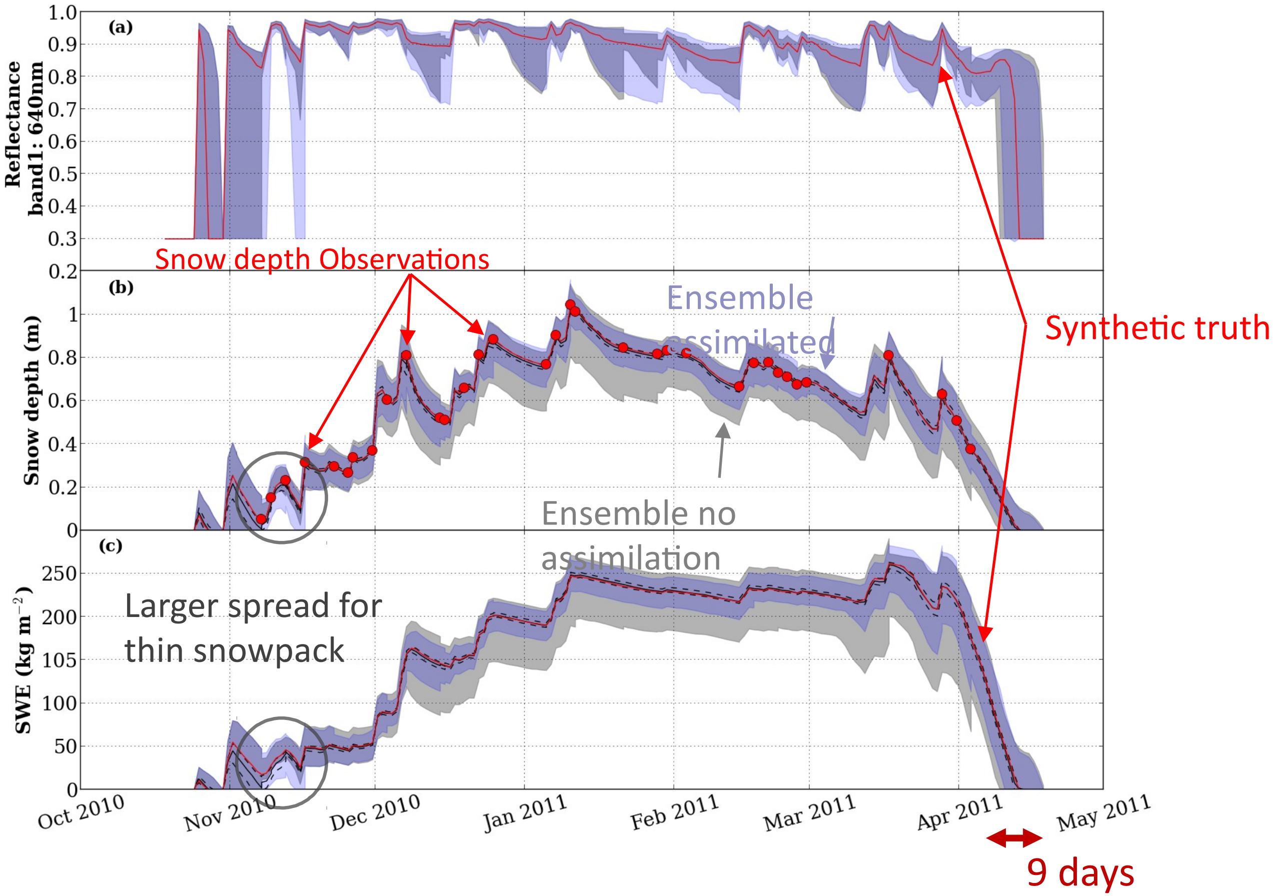
- Assimilation of both combined
  - Might be useful to mitigate limitations of these 2 kinds of observational datasets

- Assimilation of Real MODIS data
  - Need to compare model and MODIS with in situ measurements
  - Too rapid melting in Crocus simulation

Thank you

Assimilation of snow depth data (synthetic)

Same setup than baseline experiment



RMSE reduction by a factor of 3,5 compared to ensemble without assimilation

Results

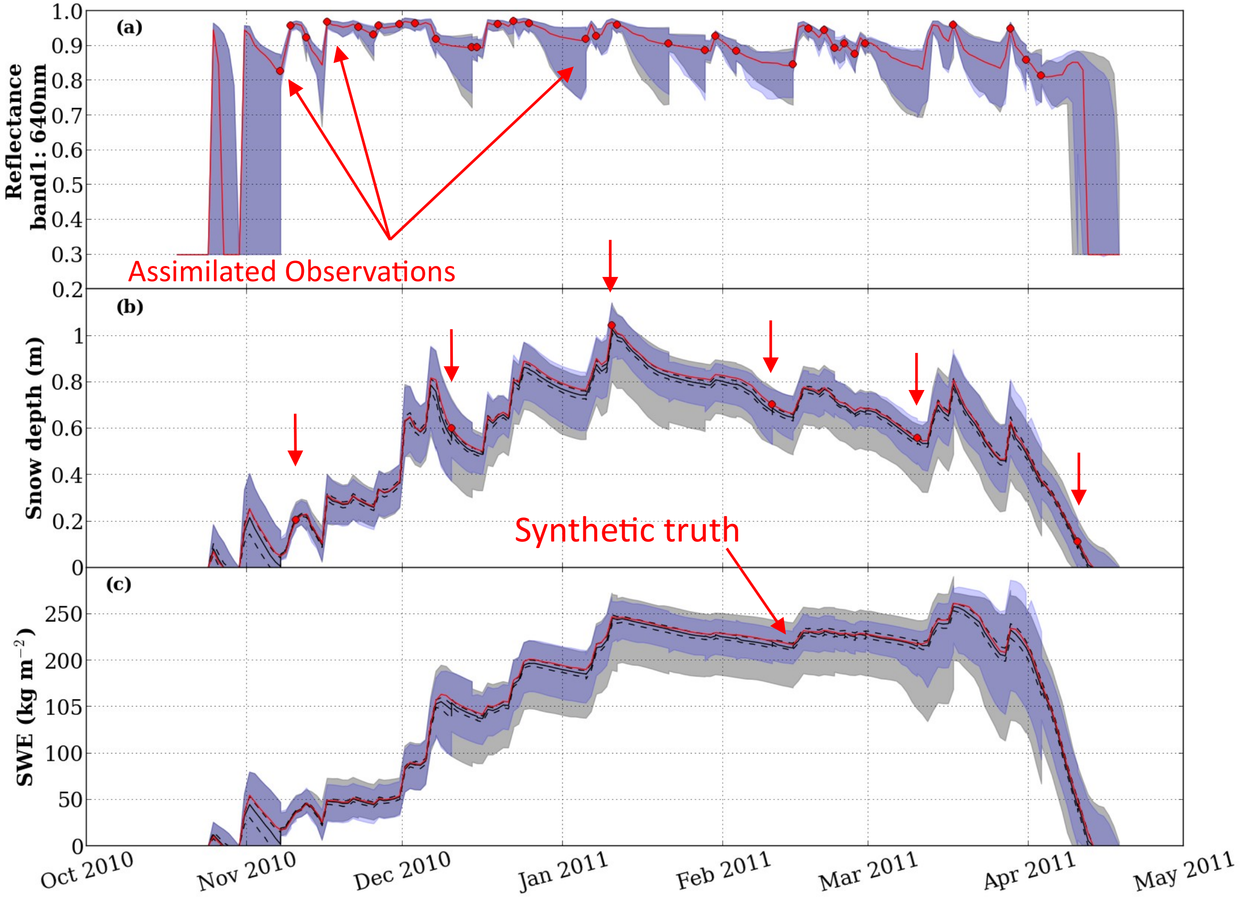
+

- The RMSE after DA is always lower than prior DA
- Date of complete snow disappearance, 9 days range against 11 days for ensemble with reflectance DA and 24 days without DA

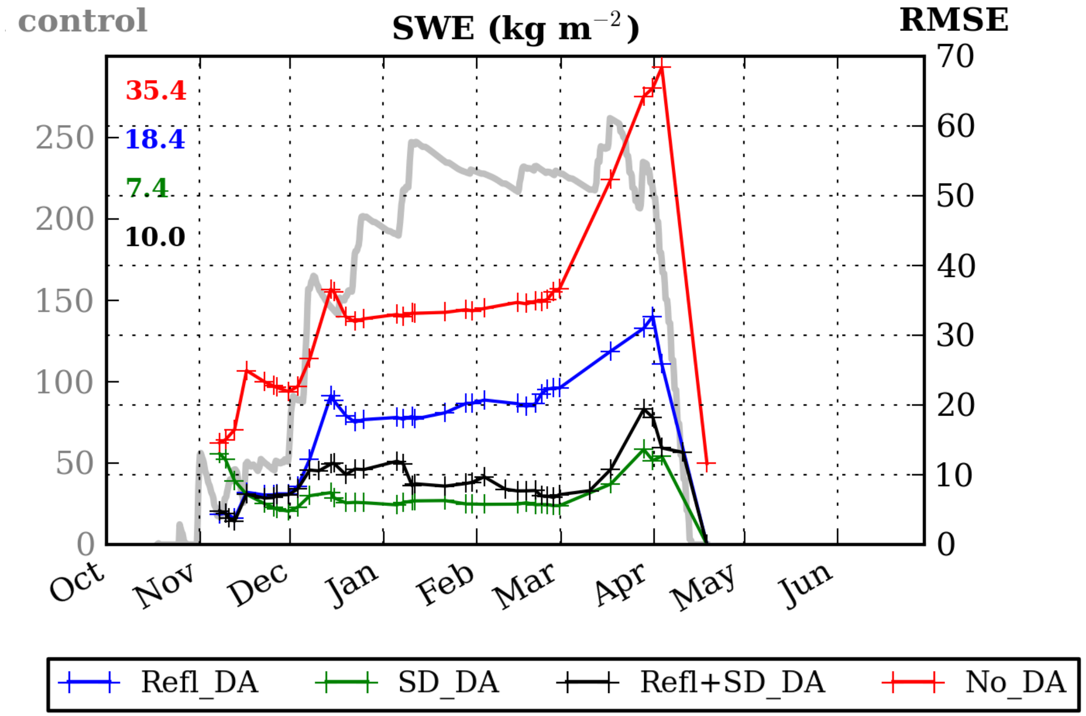
−

- Compared to ensemble with reflectance DA, larger spread for the beginning of seasons
- Less efficient for thin snow cover
- Not spatial information with this observation

Assimilation of both combined

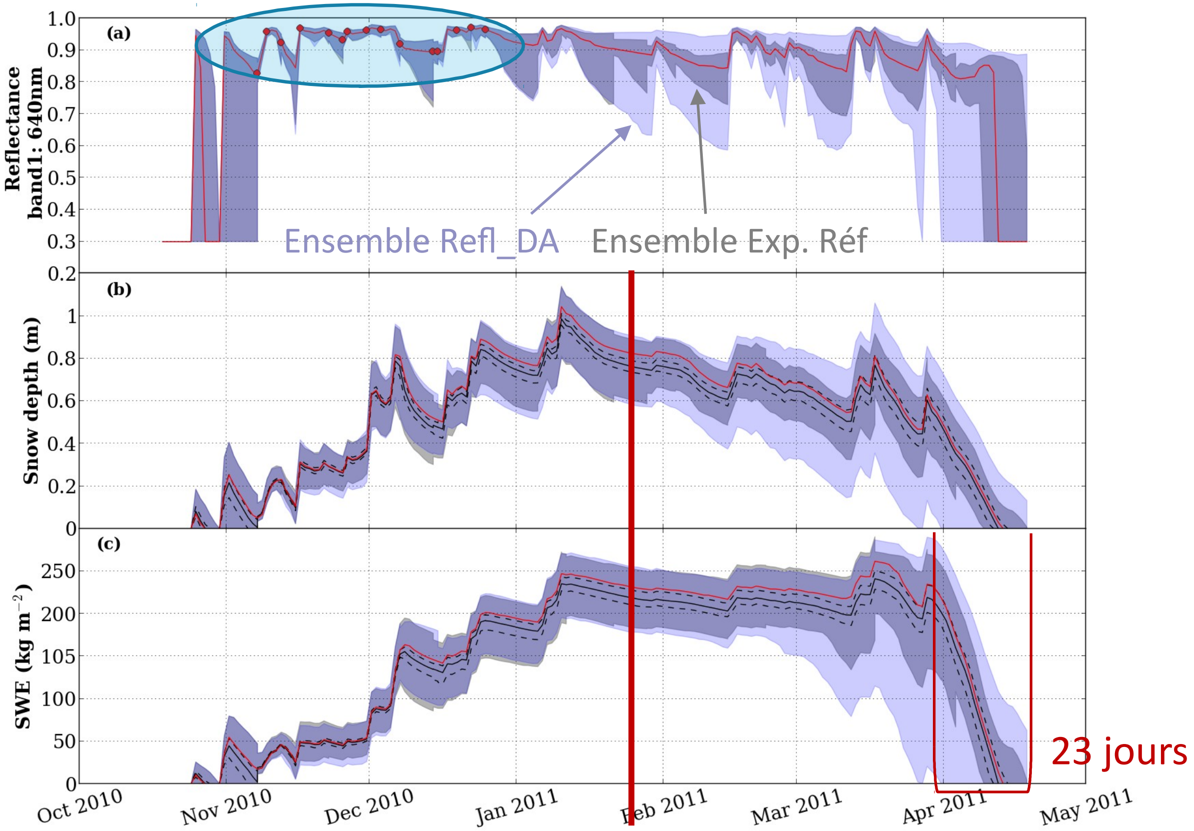


Better than Reflectance only, less than snow depth only

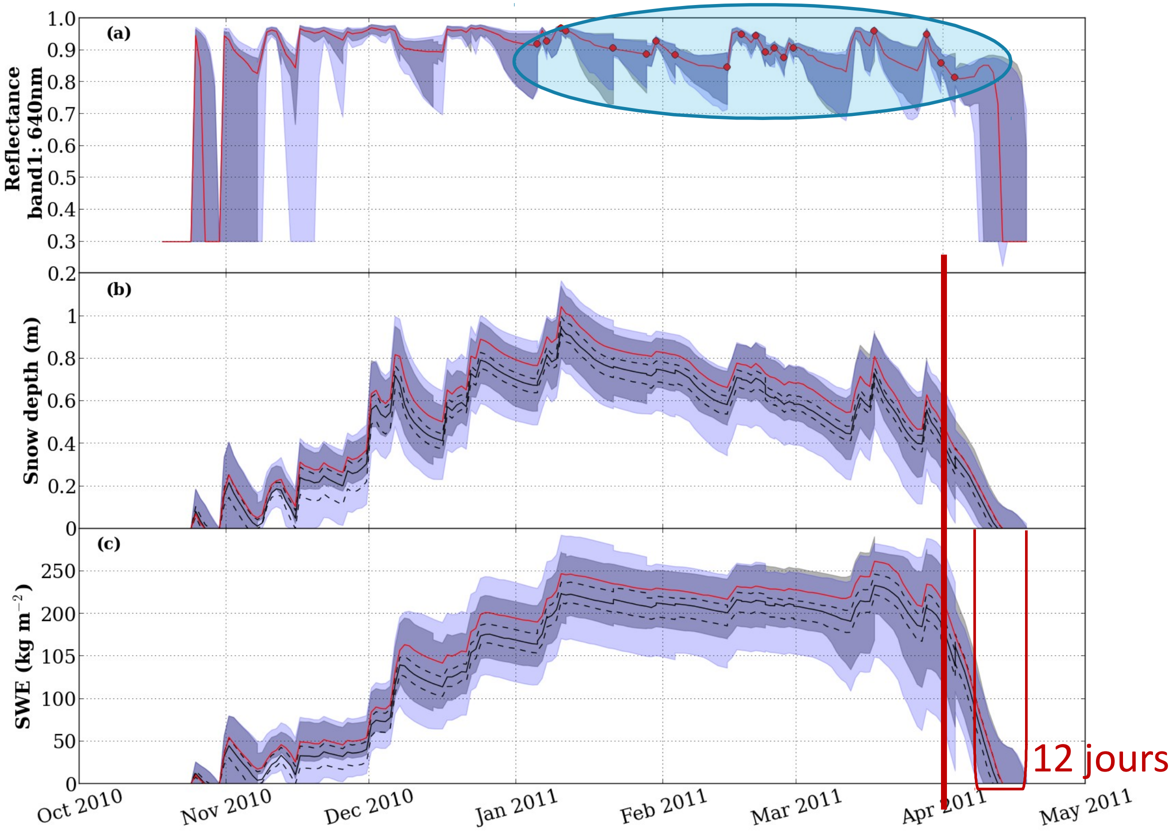


Sensibilité timing des observations

Assimilation jusqu'au 31/12/2010



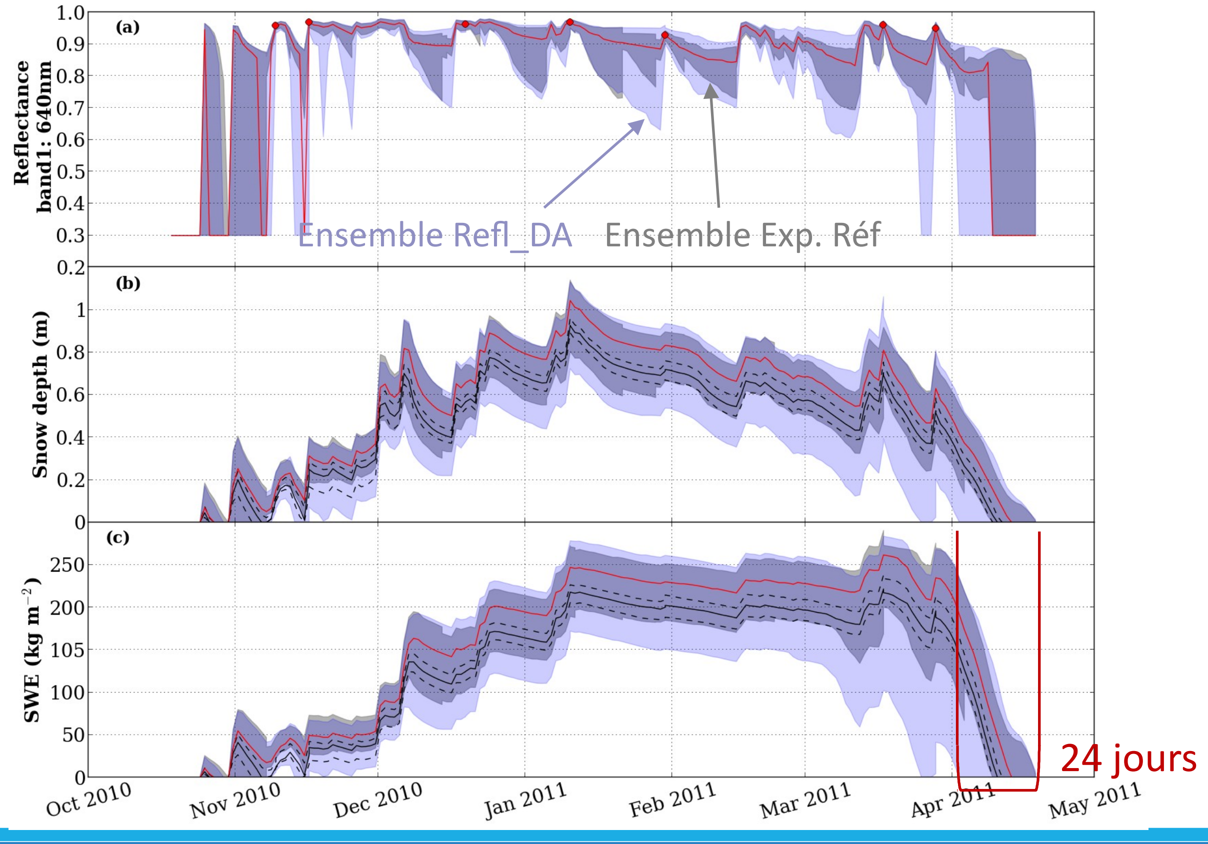
Assimilation après le 31/12/2010



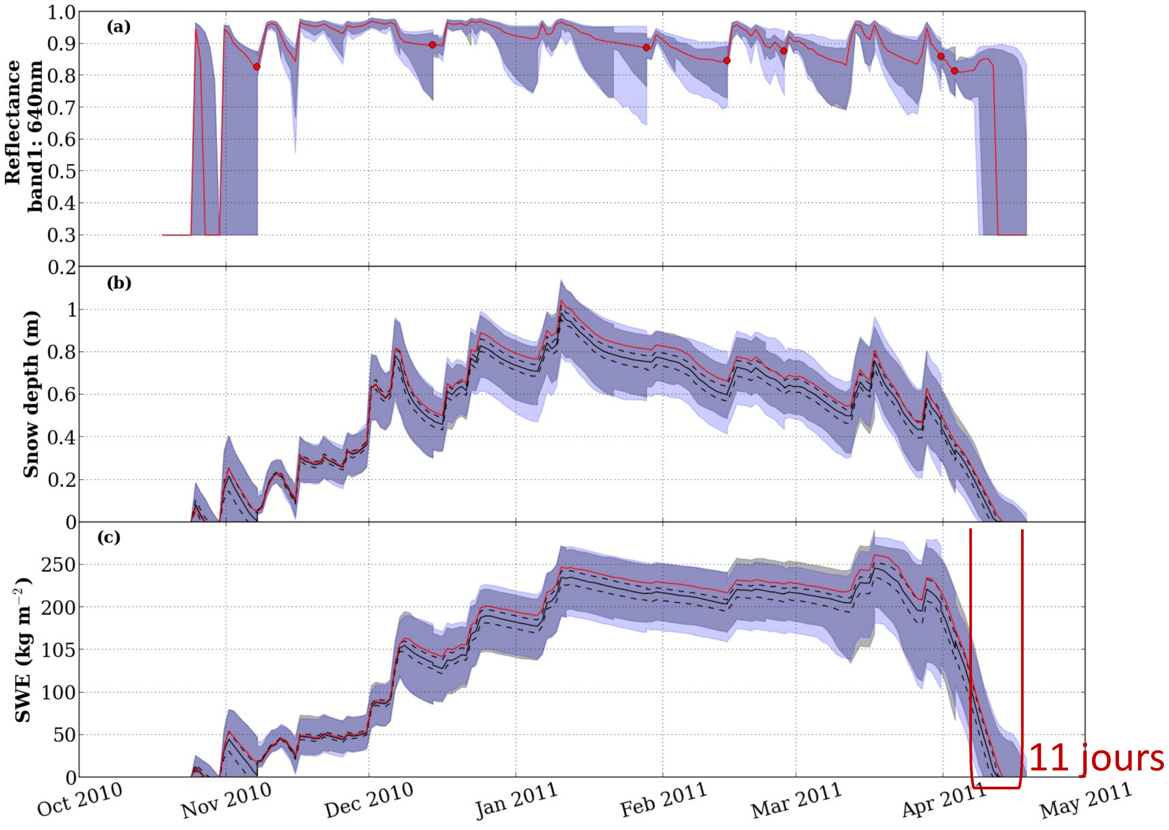
- No DA
- **Reflectance DA**
- Snow depth DA

En utilisant 7 observations…

Assimilation pendant précipitations



Assimilation après une phase sans précipitaions



Ensemble de forçages météo perturbés

Méthode de perturbation

First Order Auto Regressive model: AR(1)

$$X_t = c + \varphi X_{t-1} + \varepsilon_t \qquad \varepsilon_t \approx \mathcal{N}(0,\sigma^2)$$

Incertitude de chaque forcage

Statistiques sur 18 ans entre obs & données simulées (SAFRAN)➔ σ^2

Méthode **Additive** ou **multiplicative** pour générer l'ensemble de forcage météo

Ensemble perturbés comprenant :

- Air Temperature
- Shortwave Radiation
- Longwave Radiation
- Snow/Rain fall
- Wind speed