ECMWF Data Assimilation Training course

Land Surface Data Assimilation

Patricia de Rosnay

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Land Surface Data Assimilation

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Land surface processes

- Why it is important in NWP?
- What are the variables we are analysing?
 - How do we analyse them?
 - Which observations are used?

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Outline

Part I (Monday 16 March)

Introduction

- Snow analysis
- Screen level parameters analysis

Part II (Tuesday 17 March)

- Soil moisture analysis
- Summary and future plans



Introduction: Land Surface in NWP

- Land surfaces: Boundary conditions at the lowest level of the atmosphere
- Land surface processes \rightarrow Continental hydrological cycle, interaction with the atmosphere on various time and spatial scales, strong heterogeneities
- Crucial for near surface weather conditions, whose high quality forecast is a key objective in NWP
- Land Surface Models (LSMs) prognostic variables include:
 - Soil moisture
 - Soil temperature
 - Snow water equivalent, snow temperature, snow density
- Land surface initialization: Important for NWP & Seasonal Prediction (Beljaars et al., Mon. Wea. Rev, 1996, Koster et al., 2004 & 2011)



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Introduction: ECMWF Integrated Forecasting System (IFS) data assimilation system







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- <u>Approaches</u>: Cressman (DWD, ECMWF ERA-I), 2D Optimal Interpolation (OI) (ECMWF, CMC, JMA)
- <u>Observations</u>: *in situ* snow depth and NOAA/NESDIS IMS Snow Cover

Soil Moisture analysis

- <u>Approaches</u>:
 - -1D Optimal Interpolation (Météo-France, CMC, ALADIN and HIRLAM)
 - Analytical nudging approach (BoM)
 - Simplified Extended Kalman Filter (EKF) (DWD, ECMWF, UKMO)
- <u>Conventional observations</u>: SYNOP data of 2m air relative humidity and air temperature ; **Dedicated 2D OI screen level parameters analysis**
- <u>Satellite data</u>: ASCAT soil moisture (UKMO), SMOS (dvpt ECMWF, UKMO, Env.Canada)

Soil Temperature and Snow temperature also analysed

- 1D OI for the first layer of soil and snow temperature (ECMWF, Météo-France)

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Introduction: LDAS tasks organisation

IFS cycle 40r1 is the current operational cycle



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LDAS components and tasks organisation



(b)



LDAS & 4D-Var are run separately

LDAS

- 2D OI: Screen-level for T and humidity, Snow depth
- SEKF: Soil moisture
- 1D OI: Snow & soil temperature

Analysed surface fields: used as initial conditions for the next forecast

→ Influence the forecast which will be used as first guess for the next data assimilation window, for both 4D-Var and LDAS

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→ Feedback to the atmosphere

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Snow data assimilation

Snow Model: Component of H-TESSEL

(Balsamo et al., JHM 2009, Dutra et al., 2010)

- Snow depth S (m) (diagnostic)
- Snow water equivalent SWE (m), ie snow mass]
- Snow Density ρ_s , between 100 and 400 kg/m³

Prognostic variables

$S = \frac{1000.SWE}{\rho_s} [m]$ **Observations types used:**

- Conventional snow depth data: SYNOP and National networks
- Snow cover extent: NOAA NESDIS/IMS daily product (4km)

Drusch et al. JAM, 2004 ; de Rosnay et al, SG 2013 de Rosnay et al. Res. Mem. R48.3/PdR/1028 2010, and Res. Mem. R48.3/PdR/1139 2011

Data Assimilation Approaches:

- Cressman Interpolation in ERA-Interim
- Optimal Interpolation in operations de Rosnay et al, Survey of Geophysics 2013



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NOAA/NESDIS IMS Snow extent data

Interactive Multisensor Snow and Ice Mapping System

- Time sequenced imagery from geostationary satellites
- AVHRR,
- SSM/I
- Station data

Northern Hemisphere product

- Daily, no time stamp
- Polar stereographic projection

Information content: Snow/Snow free

Data used at ECMWF:

- **24km product in Grib** Used in ERA-Interim (2004-present) and in operations (2004-2010)
- 4 km product in Ascii
 Revised pre processing
 Used in operations (Nov 2010-present)



IMS Snow Cover 5 Feb. 2014

More information at: http://nsidc.org/data/g02156.html

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Snow Cover 24km vs 4km product



- IMS Products after pre-processing at ECMWF
- Coast mask applied in the 24km product (lack of geolocation information in the grib product)
- Data thinning (1/36) of the 4km product -> same data quantity, improved quality

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- 4km product provides more local information than 24km product
- ightarrow consistent with the way IMS is used in the data assimilation system

Snow SYNOP

2014 01 01 at 06UTC





Snow SYNOP and National Network data

2014 01 01 at 06UTC



Additional data from national networks from 7 countries:

Sweden (>300), Romania(78), The Netherlands (33), Denmark (43), Hungary (61), Norway (183), Switzerland (332).

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→ Dedicated BUFR

(de Rosnay et al. ECMWF Res. Memo, R48.3/PdR/1139, 2011)



SYNOP Snow depth availability

ECMWF Operational monitoring of SYNOP snow depth: number of observations on 2014 01 04 at 00UTC (21-09 UTC): observations gap in USA, China and southern hemisphere

http://www.ecmwf.int/products/forecasts/d/charts/monitoring/conventional/snow/





GCW Snow Watch initiative to improve in situ snow depth data access (NRT and rescue), Brun et al 2013



Snow depth observations

Snow depth observations available (>4500 per day in winter time)





Snow Analysis at ECMWF

Pre-Processing:

- SYNOP reports converted into BUFR files.
- IMS converted to BUFR (and orography added)
- SYNOP BUFR data is put into the ODB (Observation Data Base)

Snow depth analysis at 00, 06, 12, 18 UTC :

- Cressman interpolation: Operations: 1987-2010

Still used in ERA-Interim

 $\sigma_{\rm h}$ = 3 cm

IMS

- Optimal Interpolation (OI): Operational since November 2010

(de Rosnay et al; SG 2013)

Use NESDIS IMS data in the OI (00 UTC):

NESDIS: 1 st Guess:	Snow	No Snow
Snow	Х	DA 5cm
No Snow	DA	DA

enter the analysis with a snow depth of 0 cm (snow free) or 5 cm (snow covered, used only if the model first guess is snow free)

Observation errors:
SYNOP
$$\sigma_{SYNOP}$$
=4cm

Background error:



 σ_{ims} =8cm

Snow depth Optimal Interpolation

Used at CMC, JMA, ECMWF

Based on Brasnett, j appl. Meteo. 1999

- Observed first guess departure (obs.-fg), [ΔS_i] are computed from the interpolated background at each observation location [i]
- The analysis increments $[\Delta S_i^a]$ at each model grid-point [j] are then expressed as :

$$\Delta \mathbf{S}_{j}^{\mathbf{a}} = \sum_{i=1}^{N} \mathbf{w}_{i} \times \Delta \mathbf{S}_{i}$$

- The optimum weights $[w_i]$ are given for each grid point j by $|\mathbf{w} = (\mathbf{B} + \mathbf{R})^{-1} \times \mathbf{b}$
- b ; the vector of correlation coefficients of the background field error between the observations and the grid point
- B ; the correlation coefficient matrix of background field errors between all pairs of observations
- **R** ; the covariance matrix of observational errors

 σ_{b} the standard deviation of background errors (3cm), σ_{o} that of observation errors (4cm in situ, 8cm IMS)



Snow depth Optimal Interpolation

Used at CMC, JMA, ECMWF

Based on Brasnett, j appl. Meteo. 1999

 The correlation coefficients of B and b are vital to the method and are assumed to have the form (structure function)

$$\mu(i_1, i_2) = (1 + \frac{r_{i_1 i_2}}{Lx}) \exp\left(-\left[\frac{r_{i_1 i_2}}{Lx}\right]\right) \exp\left(-\left[\frac{z_{i_1 i_2}}{Lz}\right]^2\right)$$

- $r_{i1,i2}$ and $Z_{i1,i2}$ the horizontal and vertical distances between points i_1 and i_2
- Lz: vertical length scale: 800m, Lx: horizontal length scale: 55km
- Quality Control: reject observation if $\Delta S_i > Tol (\sigma_b^2 + \sigma_o^2)^{1/2}$ with Tol = 5
- ➔ Observation rejected if first guess departure larger than 25 cm
- ➔ Redundancy rejection: use observation reports closest to analysis time (use a maximum of 50 observations per grid point)



OI vs Cressman

In both cases: $\Delta S_j^a = \sum_{i=1}^{N} w_i \times \Delta S_i$

Cressman (1959): weights are function of horizontal and vertical distances. Do not account for observations and background errors.

OI: The correlation coefficients of B and b follow a second-order autoregressive horizontal structure and a Gaussian for the vertical elevation differences.

OI has longer tails than Cressman and considers more observations. Model/observation information optimally weighted using error statistics.



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Some issues in the Cressman Snow analysis

"Bull's eyes" (or "PacMan") Snow Patterns where observations are scarce Due to the Cressman interpolation (as indicated in Kalnay, 2003)



²⁰⁰⁷

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Validation data: NWS/COOP

- NWS Cooperative Observer Program
- Independent data relevant for validation
- Used to validate a set of numerical experiments considering different assimilation approaches and IMS snow cover

Numerical Experiments	Bias (cm)	R	RMSE (cm)	
Cressman, IMS 24 km	1.1	0.66	18.0	- Oper until Nov 2010 - ERA-Interim
OI, IMS 24 km	- 2.0	0.74	10.1	
OI, IMS 4km	- 2.1	0.73	10.3	
OI, IMS 4km <1500m	- 1.5	0.74	10.1	- Oper since Nov 2010

Validation against ground data

→ Main improvement due to the OI compared to Cressman

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Validation data: NWS/COOP

- NWS Cooperative Observer Program
- Independent data relevant for validation

- Used to validate a set of numerical experiments considering different assimilation approaches and IMS snow cover

RMSE (cm) for the new snow analysis (OI, IMS 4km except in mountainous areas)



Impact on the Atmospheric Forecasts



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Snow Analysis latest improvements

- 2010: replace Cressman by OI and improved IMS use (4km data and revised preprocessing)
- 2013: further improvement in the ECMWF snow analysis in IFS 40r1:

-Revised observations error specification for IMS snow cover and assimilation of 5cm of snow instead of direct insertion, -Generic snow blacklist,

-Revised surface analysis code and Observation data base (ODB) feedback

- New Land surface observations monitoring for conventional and IMS data

https://software.ecmwf.int/wiki/display/LDAS/Land+Surface+Observations+monitoring



Snow Analysis latest improvements Improved use of NESDIS/IMS snow cover data



Snow Analysis latest improvements Improved use of NESDIS/IMS snow cover data

Previous version: IFS Cycle 38r2



Snow analysis latest improvements: Temperature FC verification

Tropics

NH extra-tropics



Snow observations monitoring



Global first guess departure

Global analysis departure

Standard deviation of departure statistics

Number of in situ observations used: ~600 to 2500 per 12 hours





Summary on Snow Analysis

Large sensitivity of atmospheric forecasts to snow data assimilation (DA method, observations pre-processing, error specification)

Current snow analysis based on 2D-OI (CMC, JMC, ECMWF), old approach was based on Cressman (still used in ERA-Interim)

Importance of in situ snow depth data availability

Scarce snow depth observations in some areas → European initiative (new BUFR for additional snow data) – action to extend it to WMO Member States

- Snow cover data used (NOAA/NESDIS IMS product)
- No use of Snow Water Equivalent product in NWP
- Future investigations on using satellite radiances



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IFS cycle 40r1 is the current operational

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Screen Level parameters analysis

Screen level variables: 2m Air Temperature (T2m) and air Relative humidity (RH2m), both diagnostic variables.
Analysis based on an Optimal Interpolation using SYNOP observations, every six hours: 00UTC, 06UTC, 12UTC, 18UTC.

Screen level analysis increments are used for the soil moisture analysis (OI system, e.g. at Météo-France and ECMWF ERA-Interim),
Screen level analysis fields are used as input of the SEKF soil moisture analysis (ECMWF)

- T2m and RH2m are diagnostic variables of the model, so their analysis only has an indirect effect on atmosphere through the soil and snow variables.

- Relevance of screen level analysis for evaluation purposes



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OI Screen Level parameters analysis

Mahfouf, J. Appl. Meteo. 1991, & ECMWF News Lett. 2000

Same approach as snow analysis:

- Observed first guess departure (obs.-fg), [∆S_i] are computed from the interpolated background at each observation location [i]
- The analysis increments $[\Delta S_i^a]$ at each model grid-point [j] are then expressed as :

$$\Delta \mathbf{S}_{j}^{a} = \sum_{i=1}^{N} \mathbf{w}_{i} \times \Delta \mathbf{S}_{i}$$

- The optimum weights $[w_i]$ are given for each grid point j by $w = (B + R)^{-1} \times b$
- b ; the vector of correlation coefficients of the background field error between the observations and the grid point
- B ; the correlation coefficient matrix of background field errors between all pairs of observations
- **R** ; the covariance matrix of observational errors

 $\sigma_{\rm b}$ the standard deviation of background errors (1.5 K / 5 % RH) $\sigma_{\rm o}$ that of observation errors (2 K / 10 % RH)



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OI Screen Level parameters analysis

Mahfouf, J. Appl. Meteo. 1991, & ECMWF News Lett. 2000



Figure 9.3 Horizontal structure functions used in the Optimum Interpolation scheme for the screen level parameters and snow depth analyses.

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Screen Level parameters analysis

Quality control:

• Number of observations N = 50, horizontal length parameter d = 300 km, scanned radius 1000km

- Gross quality checks as rH \in [0,100] and T > T_{dewpoint}
- Observation points that differ more than 300 m from model orography are rejected
- First-guess check:

 Observation is rejected if :

$$|\Delta X_{i}| = \gamma \sqrt{\sigma_{o}^{2} + \sigma_{b}^{2}}$$

$$\Delta X_{i}| > \gamma \sqrt{\sigma_{o}^{2} + \sigma_{b}^{2}}$$
 with $\gamma = 3$ (tolerance)

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- Redundancy rejection
- Number of active observations > 16000 per 12 hour (less than 20% of the available observations)

Screen level observations

All T2m observations available (>180000 per day)



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Screen level observations monitoring



2014

Global first guess departure

Global analysis departure

Standard deviation of departure statistics

Number of observations used: >16000 per 12 hours





Screen level observations monitoring



1200--0-

18

21 24 27

30 2

5 8

Europe first guess departure

Europe analysis departure

Standard deviation of departure statistics

Number of observations used over Europe: ~5000 per 12 hours



23 26 1 Mar

11 14 17 20

1D OI soil and snow temperature analysis

• Analysis increments from 2-m temperature analysis are used to produce increments for the first layer soil temperature and snow temperature $\Delta T = c(T_a - T_b)$ $c = (1 - F_1)F_3$

The analysis increments **c** relies on two empirical functions that account for (F_1 ,) the cosine of the mean solar zenith angle (μ_M) and (F_3) the model orography (to reduce the increments over mountainous areas where observations are considered less reliable)

dC

$$F_{1} = \frac{1}{2} \{1 + \tanh[\lambda(\mu_{M} - 0.5)]\}, \quad \lambda = 7$$

$$F_{3} = \begin{cases} 0 \ if \ Z > Z_{max} \\ \left(\frac{Z - Z_{max}}{Z_{min} - Z_{max}}\right)^{2} \ if \ Z_{min} < Z < Z_{max} \\ 1 \ if \ Z < Z_{min} \end{cases}$$

$$G_{1} = \frac{1}{2} \{1 + \tanh[\lambda(\mu_{M} - 0.5)]\}, \quad \lambda = 7$$

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Where Z is the model orography, Z_{min} =500m and Z_{max} =3000m.

c is constructed such that the analysis of soil temperatures is more effective during night and in winter when the temperature errors are less likely to be related to soil moisture

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Screen level analysis: 2m temperature forecast verification



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LDAS: "Bring home" messages

Land surface processes

- Boundary conditions at the lowest level of the atmosphere
- Crucial for numerical weather and climate predictions

Analysed surface fields

- Used as initial conditions for the next forecast
- ➔ Influence the fc be used as first guess for the next DA window
- **Snow analysis:** 2D-OI for snow depth
 - Conventional snow depth data: SYNOP and National networks
 - Snow cover extent: NOAA NESDIS/IMS daily product (4km)
- Screen Level analysis: 2D-OI for T2m, RH2m
 - Analysis fields used as input of the SEKF soil moisture analysis
 - T2m increments: inputs of the 1D-OI soil & snow temperature analysis



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Introduction: LDAS tasks organisation



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Snow depth Optimal Interpolation

Used at CMC, JMA, ECMWF

Based on Brasnett, j appl. Meteo. 1999

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- 1. Observed first guess departure ΔS_i are computed from the interpolated background at each observation location i.
- 2. Analysis increments ΔS_j^a at each model grid point j are calculated from: $\Delta S_j^a = \sum_{i=1}^{N} w_i \times \Delta S_i$
- 3. The optimum weights w_i are given for each grid point j by: (**B** + **O**) **w** = **b**
 - **b** : **background error vector** between model grid point j and observation i (dimension of N observations) $b(i) = \sigma_{b}^2 \mu(i,j)$
 - B : correlation coefficient matrix of background field errors between all pairs of observations (N × N observations)

B(i₁,i₂) = $\sigma_b^2 \times \mu(i_1,i_2)$ with the horizontal correlation coefficients $\mu(i_1,i_2)$ and σ_b = 3cm the standard deviation of background errors.

O : covariance matrix of the observation error (N × N observations): $O = \sigma_0^2 \times I$

with σ_o the standard deviation of observation errors (4cm in situ, 8cm IMS)

Snow depth Optimal Interpolation

Used at CMC, JMA, ECMWF

Based on Brasnett, j appl. Meteo. 1999

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Correlation coefficients $\mu(i_1, i_2)$ (structure function):

$$\mu(i_1, i_2) = (1 + \frac{r_{i_1 i_2}}{Lx}) \exp\left(-\left[\frac{r_{i_1 i_2}}{Lx}\right]\right) \exp\left(-\left[\frac{z_{i_1 i_2}}{Lz}\right]^2\right)$$

Lz; vertical length scale: 800m, **Lx:** horizontal length scale: 55km $r_{i1,i2}$ and $Z_{i1,i2}$ the horizontal and vertical distances between points i1 and i2

Quality Control: reject observation if ΔS_i > Tol $(\sigma_b^2 + \sigma_o^2)^{1/2}$ with Tol = 5 →Observation rejected if first guess departure larger than 25 cm

Redundancy rejection: use observation reports closest to analysis time And use a maximum of 50 observations per grid point)

OI Screen Level parameters analysis

Mahfouf, J. Appl. Meteo. 1991, & ECMWF News Lett. 2000

Same approach as snow analysis:

1. First guess departure ΔX_i estimated at each observation location i from the observation and the interpolated background field (6 h or 12 h forecast).

2. Analysis increments ΔX_i^a at each model grid point j are calculated from:

$$\Delta \mathbf{X}_{j}^{a} = \sum_{i=1}^{N} \mathbf{w}_{i} \times \Delta \mathbf{X}_{i}$$

- 3. The optimum weights w_i are given by: $(\mathbf{B} + \mathbf{O}) \mathbf{w} = \mathbf{b}$
 - **b** : error covariance between observation i and model grid point j (dimension of N observations)
 - **B** : error covariance matrix of the background field (N × N observations) $B(i_1,i_2) = \sigma_b^2 \times \mu(i_1,i_2)$ with the horizontal correlation coefficients $\mu(i_1,i_2)$ and $\sigma_b = 1.5$ K / 5 % rH the standard deviation of background errors.

$$\mu(\mathbf{i}_1, \mathbf{i}_2) = \exp\left(-\frac{1}{2}\left[\frac{\mathbf{r}_{\mathbf{i}_1\mathbf{i}_2}}{\mathbf{d}}\right]^2\right)$$

Horizontal correlation coefficients (structure functions)

O : covariance matrix of the observation error (N × N observations): **O** = $\sigma_0^2 \times I$ with $\sigma_0 = 2.0$ K / 10 % rH the standard deviation of obs. errors

ECM

Summary on Snow Analysis

- The snow analysis is a 2-D OI performed every 6 hours, at 00 UTC, 06 UTC, 12 UTC and 18 UTC
- The snow-depth background S (m) is estimated from the shortrange forecast of snow water equivalent (m of water equivalent) and snow density (units: kgm⁻³)
- Analysis is performed using snow-depth observations, the snowdepth background field, and the high resolution (4km) NOAA/NESDIS snow extent
- Snow depth observations include conventional snow depth reports from SYNOP stations as well as additional national snow depth observations reported by several member states



Summary on Snow Analysis

- the satellite derived snow extent is used once per day, for the 00 UTC analysis
- It is converted in the Observation Data Base into a quantitative snow depth information
- To this end the model relation between snow extent and snow depth is used as observation operator, with 5 cm of snow depth where binary snow cover is one and 0 cm snow depth where binary snow cover is zero
- The latter observations enter the analysis whatever the first guess conditions are
- In contrast the 5 cm snow depth derived from the snow cover observations enter the analysis only where the model first guess indicates snow free conditions



Soil Moisture analysis at 00:00, 06:00, 12:00, 18:00





Schematic depiction of the interaction between the soil hydrology and the atmosphere: illustrates the behaviour of the soil and the atmosphere within a complete cycle (wet period followed by a dry period) [Dooge 1992]



Impact of soil moisture on precipitation : Koster et al., Science, 2004

The GLACE Team: *Regions of Strong Coupling Between Soil Moisture and Precipitation*. **Science** 20 August 2004: Vol. 305 no. 5687 pp. 1138-1140 DOI: 10.1126/science.1100217

Multimodel estimation of land atmosphere coupling strength :

A global initialization of soil moisture may enhance precipitation prediction skill during Northern Hemisphere summer (*in the transition zones between wet and dry climates*) Land-atmosphere coupling strength (JJA), averaged across AGCMs



Multimodel estimation of the regions on Earth where precipitation is affected by soil moisture anomalies during Northern Hemisphere summer [*Koster et al., Science, 2004*]



Soil Moisture analysis at 00:00, 06:00, 12:00, 18:00



Model first guess for analysis at $00:00 (d) \rightarrow Fc \ 18:00 (d-1) \text{ step } 6$ Model first guess for analysis at 06:00 (d) \rightarrow Fc 18:00 (d-1) step 12 ... ECMV

ECMWF Training course - Surface analysis Part I 16 March 2015