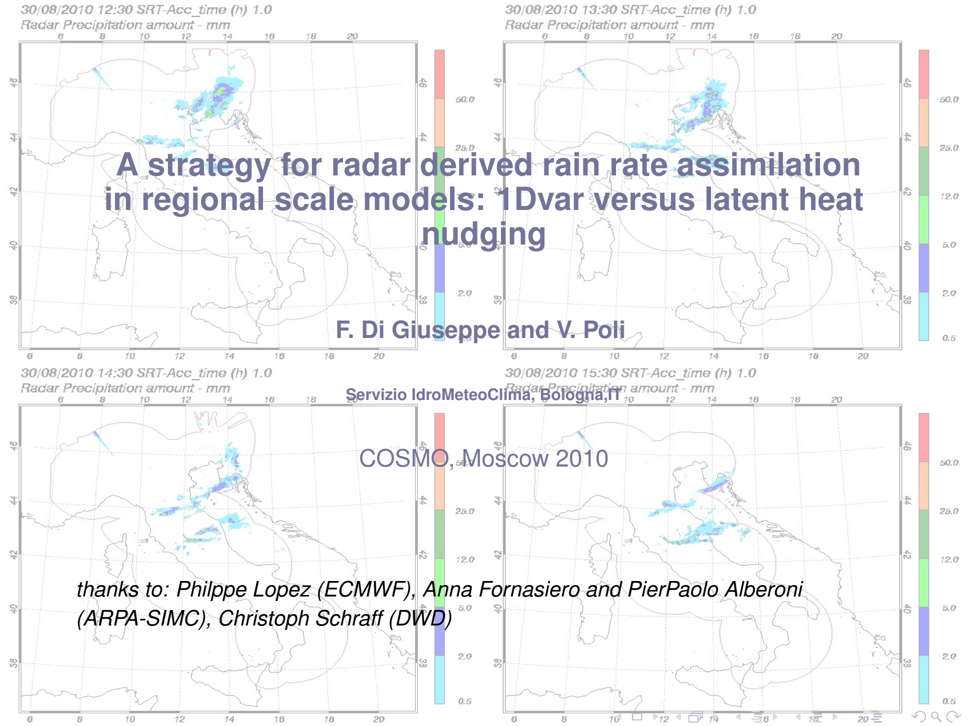


A strategy for radar derived rain rate assimilation in regional scale models: 1Dvar versus latent heat nudging

F. Di Giuseppe and V. Poli

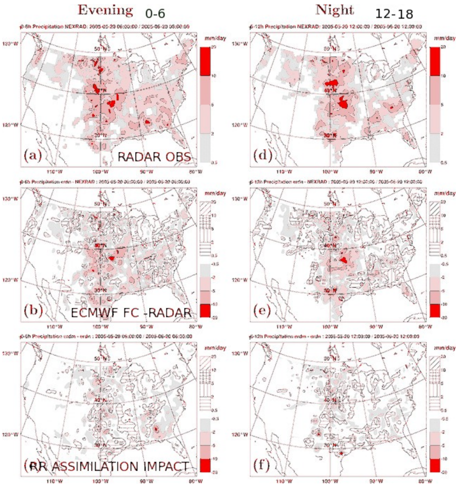
Servizio IdroMeteoClima, Bologna,IT

COSMO, Moscow 2010

thanks to: Philppe Lopez (ECMWF), Anna Fornasiero and PierPaolo Alberoni (ARPA-SIMC), Christoph Schraff (DWD)

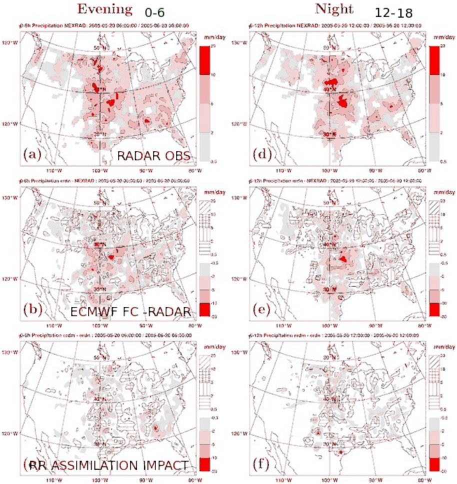
What can we expect from Radar RR assimilation?

What can we expect from Radar RR assimilation?



Maps of mean precipitation accumulations (1 month) from USA radar network (NEXRAD), differences ECMWF forecast minus NEXRAD and ECMWF forecast with RR assimilation minus CTRL. **The mean error in the model precipitation is not greatly modified by the additional NEXRAD observations, except for a further reduction of rainfall over SEasUS for the 06 h range** *Lopez P. and P. Bauer: 2006 Mon. Wea. Rev.*

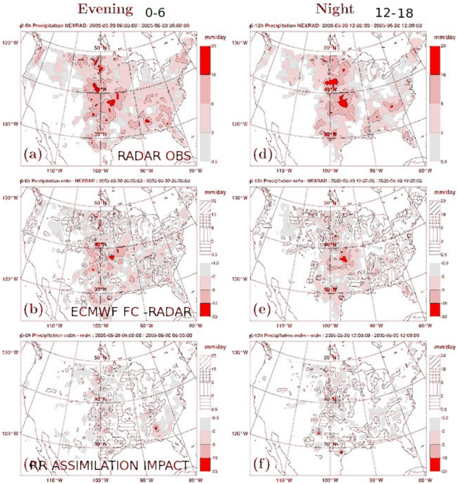
What can we expect from Radar RR assimilation?



Maps of mean precipitation accumulations (1 month) from USA radar network (NEXRAD), differences ECMWF forecast minus NEXRAD and ECMWF forecast with RR assimilation minus CTRL. **The mean error in the model precipitation is not greatly modified by the additional NEXRAD observations, except for a further reduction of rainfall over SEasUS for the 06 h range** *Lopez P. and P. Bauer: 2006 Mon. Wea. Rev.*

Other findings were that

What can we expect from Radar RR assimilation?

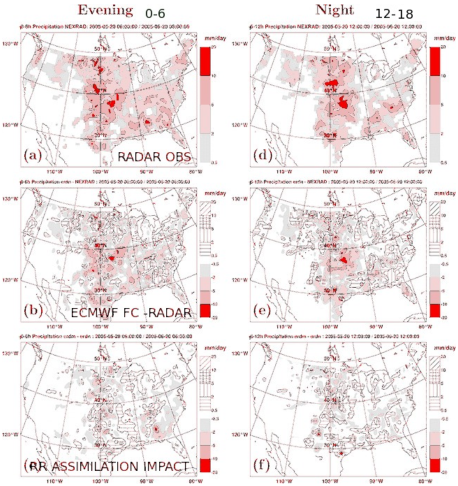


Maps of mean precipitation accumulations (1 month) from USA radar network (NEXRAD), differences ECMWF forecast minus NEXRAD and ECMWF forecast with RR assimilation minus CTRL. **The mean error in the model precipitation is not greatly modified by the additional NEXRAD observations, except for a further reduction of rainfall over SEasUS for the 06 h range** *Lopez P. and P. Bauer: 2006 Mon. Wea. Rev.*

Other findings were that

- USA have a lot of in-situ humidity obserations

What can we expect from Radar RR assimilation?

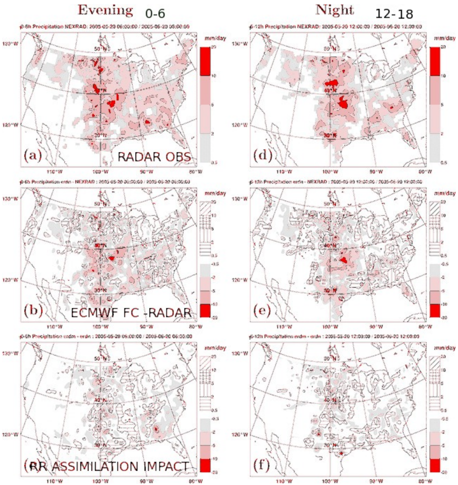


Maps of mean precipitation accumulations (1 month) from USA radar network (NEXRAD), differences ECMWF forecast minus NEXRAD and ECMWF forecast with RR assimilation minus CTRL. **The mean error in the model precipitation is not greatly modified by the additional NEXRAD observations, except for a further reduction of rainfall over SEasUS for the 06 h range** *Lopez P. and P. Bauer: 2006 Mon. Wea. Rev.*

Other findings were that

- USA have a lot of in-situ humidity obserations
- when these are actually removed from the assimilation the impact of radar observation is highly strenghtned

What can we expect from Radar RR assimilation?



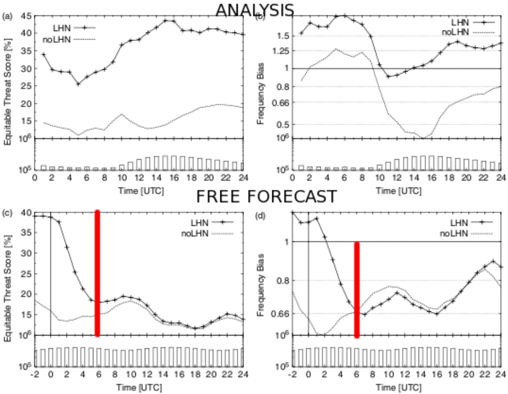
Maps of mean precipitation accumulations (1 month) from USA radar network (NEXRAD), differences ECMWF forecast minus NEXRAD and ECMWF forecast with RR assimilation minus CTRL. **The mean error in the model precipitation is not greatly modified by the additional NEXRAD observations, except for a further reduction of rainfall over SEasUS for the 06 h range** *Lopez P. and P. Bauer: 2006 Mon. Wea. Rev.*

Other findings were that

- USA have a lot of in-situ humidity obserations
- when these are actually removed from the assimilation the impact of radar observation is highly strenghtned
- therefore the use of radar data can be more important in areas less covered by observations

Lopez P. and P. Bauer: 2006 Mon. Wea. Rev.

COSMO RR assimilation



Impact of latent heat nudging for 60 days against radar observations. (COSMO-DE)

from Stephan K, Klink S, Schraff C. 2008.QJRMS

Outline

“Italian”Motivation

The Italian radar network is planned to become fully operational in 2011. The successful use of radar derived products, and in primis of the derived rain rate, is clearly desirable not only for monitoring purposes but also for the substantial data enrichment of high resolution assimilation systems based on rapid update cycles

Outline

“Italian”Motivation

The Italian radar network is planned to become fully operational in 2011. The successful use of radar derived products, and in primis of the derived rain rate, is clearly desirable not only for monitoring purposes but also for the substantial data enrichment of high resolution assimilation systems based on rapid update cycles

Latent Heat nudging

Assumption: The precipitation rate in a column is proportional to the latent heat release. If there are differences between modelled rain rates, $\mathbf{RR}_b$, and the observed ones $\mathbf{RR}_{obs}$, the scheme adds a latent heat term to the equation describing the temperature tendency.

Implementation:

The LHN temperature increment, ΔT_{LHN}, is performed by scaling the background temperature vertical profile with the ratio of analysed to modeled precipitation rate according to equation:

$$\Delta T_{LHN} = \left(\frac{RR_{ana}}{RR_b} - 1 \right) \Delta T_{LHmodel} \quad (1)$$

where the analysed precipitation rate is a weighted mean of observed and modeled precipitation rate ($\mathrm{RR}_{ana} = \beta \cdot \mathrm{RR}_{obs} + (1 - \beta) \cdot \mathrm{RR}_b$).

Latent Heat nudging

Assumption: The precipitation rate in a column is proportional to the latent heat release. If there are differences between modelled rain rates, $\mathbf{RR}_b$, and the observed ones $\mathbf{RR}_{obs}$, the scheme adds a latent heat term to the equation describing the temperature tendency.

Implementation:

The LHN temperature increment, ΔT_{LHN}, is performed by scaling the background temperature vertical profile with the ratio of analysed to modeled precipitation rate according to equation:

$$\Delta T_{LHN} = \left(\frac{RR_{ana}}{RR_b} - 1 \right) \Delta T_{LHmodel} \tag{1}$$

where the analysed precipitation rate is a weighted mean of observed and modeled precipitation rate ($RR_{ana} = \beta \cdot RR_{obs} + (1 - \beta) \cdot RR_b$).

1DVAR

Assumption: . The precipitation rate in a column is a “solution” of the large-scale and convection cloud schemes. If there are differences between modelled rain rates, $\mathbf{RR}_b$, and observed ones $\mathbf{RR}_{obs}$, a simplified linearised scheme search the best increments in the temperature and humidity profiles which minimise the RR differences taking into account the estimated error in the model and observations

Implementation:

The 1DVAR temperature and humidity increments, $\Delta T_{1DVAR}, \Delta Q_{1DVAR}$ are solutions of:

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x}-\mathbf{x}_b)^T\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b) + \\ + \frac{1}{2}(H(\mathbf{x})-\mathbf{RR_{obs}})^T\mathbf{R}^{-1}(H(\mathbf{x})-\mathbf{RR_{obs}}) \quad (2)$$

where H is the operator simulating the observed data from the model variable $\mathbf{x}$, $\mathbf{R}$ is the observation error matrix which includes measurement errors and representativeness errors, including errors in H, and $\mathbf{B}$ is the background error covariance matrix of the state $\mathbf{x}_b$. The superscripts -1 and T denote inverse and transpose matrices, respectively

1DVAR

Assumption: . The precipitation rate in a column is a “solution” of the large-scale and convection cloud schemes. If there are differences between modelled rain rates,$\mathbf{RR}_b$, and observed ones $\mathbf{RR}_{obs}$, a simplified linearised scheme search the best increments in the temperature and humidity profiles which minimise the RR differences taking into account the estimated error in the model and observations

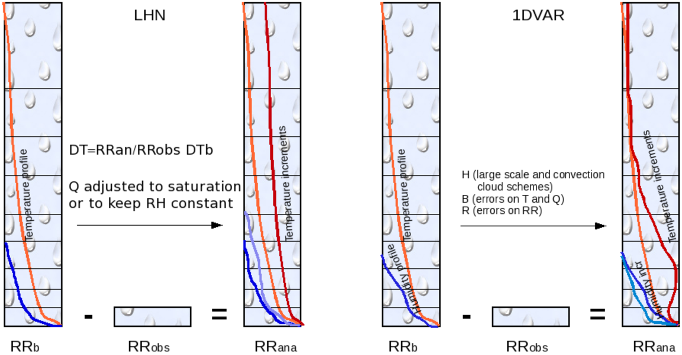
Implementation:

The 1DVAR temperature and humidity increments, $\Delta T_{1DVAR}, \Delta Q_{1DVAR}$ are solutions of:

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x}-\mathbf{x}_b)^T\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b)+ \\ +\frac{1}{2}(H(\mathbf{x})-\mathbf{RR_{obs}})^T\mathbf{R}^{-1}(H(\mathbf{x})-\mathbf{RR_{obs}}) \qquad (2)$$

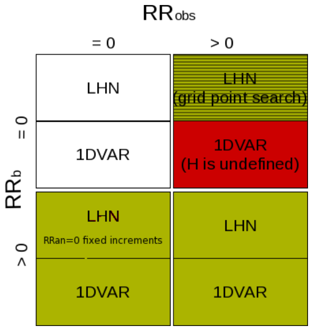
where H is the operator simulating the observed data from the model variable $\mathbf{x}$, $\mathbf{R}$ is the observation error matrix which includes measurement errors and representativeness errors, including errors in H, and $\mathbf{B}$ is the background error covariance matrix of the state $\mathbf{x}_b$. The superscripts -1 and T denote inverse and transpose matrices, respectively

Method Differences



In both cases the observation is at the ground. The LHN uses the differences in RR to rescale the whole temperature profile. The 1DVAR instead propagates “vertically “ the differences using a linearised cloud model. The 1DVAR retains information on the model and observation errors through the **B** and **R** matrices.

When they work ok and ... when they don't!



- $RR_{obs} = 0$ and $RR_b = 0$ No winner, No looser!
- $RR_{obs} > 0$ and $RR_b = 0$

  LHN $\Delta T_{LHmodel} = 0$ there can't be an increment (the algorithm applies a grid-point search for a suitable $\Delta T_{LHmodel}$ profile)

  1DVar The cloud operator H(**xb**)=0 therefore

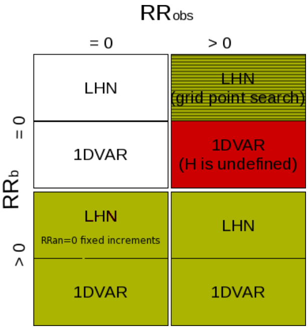
  $$J(\mathbf{x}) = \frac{1}{2}(-\mathbf{y})^T \mathbf{R}^{-1}(-\mathbf{y})$$

  which does not depend anymore on the temperature and humidity profiles. The increments are null.
- $RR_{obs} = 0$ and $RR_b > 0$

  LHN $RR_{ana}= \beta \cdot RR_{obs}+(1- \beta) \cdot RR_b = 0$!! the de-crement is setto aa fixed ammount.

  1DVar No problems! works very efficiently
- $RR_{obs} > 0$ and $RR_b > 0$ Each method plays its game !

When they work ok and ... when they don't!



- $\mathrm{RR}_{obs} = 0$ and $\mathrm{RR}_b = 0$ No winner, No looser!
- $\mathrm{RR}_{obs} > 0$ and $\mathrm{RR}_b = 0$

LHN $\Delta T_{LHmodel} = 0$ there can't be an increment (the algorithm applies a grid-point search for a suitable $\Delta T_{LHmodel}$ profile)

1DVar The cloud operator H(**xb**)=0 therefore

$$J(\mathbf{x}) = \frac{1}{2}(-\mathbf{y})^T \mathbf{R}^{-1}(-\mathbf{y})$$

which does not depend anymore on the temperature and humidity profiles. The increments are null.

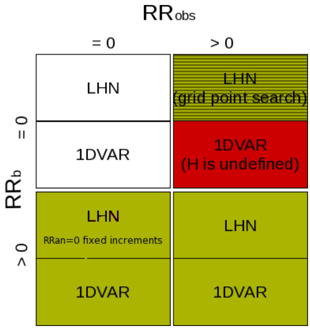
- $\mathrm{RR}_{obs} = 0$ and $\mathrm{RR}_b > 0$

LHN RR_{ana}= $\beta\cdot$ RR_{obs}+(1- β) $\cdot$ $\mathrm{RR}_b = 0$!! the de-crement is setto aa fixed ammount.

1DVar No problems! works very efficiently

- $\mathrm{RR}_{obs} > 0$ and $\mathrm{RR}_b > 0$ Each method plays its game !

When they work ok and ... when they don't!



- $RR_{obs} = 0$ and $RR_b = 0$ No winner, No looser!
- $RR_{obs} > 0$ and $RR_b = 0$

LHN $\Delta T_{LHmodel} = 0$ there can't be an increment (the algorithm applies a grid-point search for a suitable $\Delta T_{LHmodel}$ profile)

1DVar The cloud operator H(**xb**)=0 therefore

$$J(\mathbf{x}) = \frac{1}{2}(-\mathbf{y})^T \mathbf{R}^{-1}(-\mathbf{y})$$

which does not depend anymore on the temperature and humidity profiles. The increments are null.

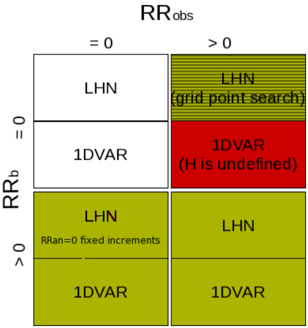
- $RR_{obs} = 0$ and $RR_b > 0$

LHN $RR_{ana}= \beta\cdot RR_{obs}+(1-\beta)\cdot RR_b = 0$!! the de-crement is setto aa fixed ammount.

1DVar No problems! works very efficiently

- $RR_{obs} > 0$ and $RR_b > 0$ Each method plays its game !

When they work ok and ... when they don't!



- $\mathrm{RR}_{obs} = 0$ and $\mathrm{RR}_b = 0$ No winner, No looser!
- $\mathrm{RR}_{obs} > 0$ and $\mathrm{RR}_b = 0$

LHN $\Delta T_{LHmodel} = 0$ there can't be an increment (the algorithm applies a grid-point search for a suitable $\Delta T_{LHmodel}$ profile)

1DVar The cloud operator H(**xb**)=0 therefore

$$J(\mathbf{x}) = \frac{1}{2}(-\mathbf{y})^T \mathbf{R}^{-1}(-\mathbf{y})$$

which does not depend anymore on the temperature and humidity profiles. The increments are null.

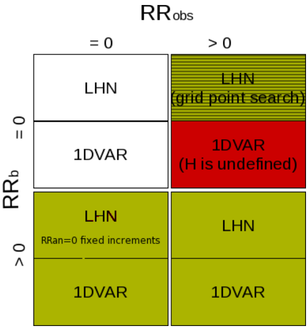
- $\mathrm{RR}_{obs} = 0$ and $\mathrm{RR}_b > 0$

LHN $\mathrm{RR}_{ana}= \beta\cdot \mathrm{RR}_{obs}+(1-\beta)\cdot \mathrm{RR}_b = 0$!! the de-crement is setto aa fixed ammount.

1DVar No problems! works very efficiently

- $\mathrm{RR}_{obs} > 0$ and $\mathrm{RR}_b > 0$ Each method plays its game !

When they work ok and ... when they don't!



- $RR_{obs} = 0$ and $RR_b = 0$ No winner, No looser!
- $RR_{obs} > 0$ and $RR_b = 0$

LHN $\Delta T_{LHmodel} = 0$ there can't be an increment (the algorithm applies a grid-point search for a suitable $\Delta T_{LHmodel}$ profile)

1DVar The cloud operator H(**xb**)=0 therefore

$$J(\mathbf{x}) = \frac{1}{2}(-\mathbf{y})^T \mathbf{R}^{-1}(-\mathbf{y})$$

which does not depend anymore on the temperature and humidity profiles. The increments are null.

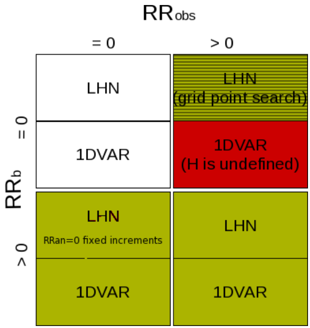
- $RR_{obs} = 0$ and $RR_b > 0$

LHN $RR_{ana}= \beta \cdot RR_{obs}+(1- \beta) \cdot RR_b = 0$!! the de-crement is setto aa fixed ammount.

1DVar No problems! works very efficiently

- $RR_{obs} > 0$ and $RR_b > 0$ Each method plays its game !

When they work ok and ... when they don't!



- $RR_{obs} = 0$ and $RR_b = 0$ No winner, No looser!
- $RR_{obs} > 0$ and $RR_b = 0$

LHN $\Delta T_{LHmodel} = 0$ there can't be an increment (the algorithm applies a grid-point search for a suitable $\Delta T_{LHmodel}$ profile)

1DVar The cloud operator H(**xb**)=0 therefore

$$J(\mathbf{x}) = \frac{1}{2}(-\mathbf{y})^T\mathbf{R}^{-1}(-\mathbf{y})$$

which does not depend anymore on the temperature and humidity profiles. The increments are null.

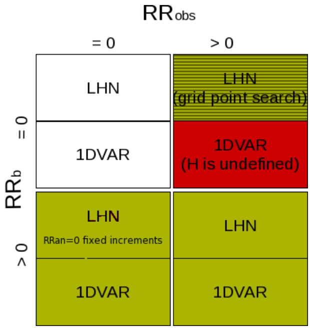
- $RR_{obs} = 0$ and $RR_b > 0$

LHN $RR_{ana} = \beta \cdot RR_{obs} + (1-\beta) \cdot RR_b = 0$!! the de-crement is setto aa fixed ammount.

1DVar No problems! works very efficiently

- $RR_{obs} > 0$ and $RR_b > 0$ Each method plays its game !

When they work ok and ... when they don't!



- $\mathrm{RR}_{obs} = 0$ and $\mathrm{RR}_b = 0$ No winner, No looser!
- $\mathrm{RR}_{obs} > 0$ and $\mathrm{RR}_b = 0$

  LHN $\Delta T_{LHmodel} = 0$ there can't be an increment (the algorithm applies a grid-point search for a suitable $\Delta T_{LHmodel}$ profile)

  1DVar The cloud operator H(**xb**)=0 therefore

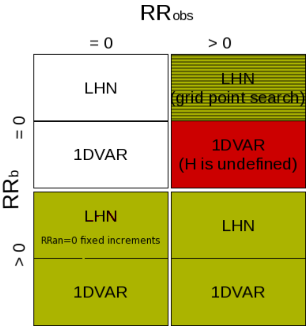
$$J(\mathbf{x}) = \frac{1}{2}(-\mathbf{y})^T \mathbf{R}^{-1}(-\mathbf{y})$$

  which does not depend anymore on the temperature and humidity profiles. The increments are null.
- $\mathrm{RR}_{obs} = 0$ and $\mathrm{RR}_b > 0$

  LHN $\mathrm{RR}_{ana}= \beta\cdot \mathrm{RR}_{obs}+(1- \beta) \cdot \mathrm{RR}_b = 0$!! the de-crement is setto aa fixed ammount.

  1DVar No problems! works very efficiently
- $\mathrm{RR}_{obs} > 0$ and $\mathrm{RR}_b > 0$ Each method plays its game !

When they work ok and ... when they don't!



- $\mathrm{RR}_{obs} = 0$ and $\mathrm{RR}_b = 0$ No winner, No looser!
- $\mathrm{RR}_{obs} > 0$ and $\mathrm{RR}_b = 0$

LHN $\Delta T_{LHmodel} = 0$ there can't be an increment (the algorithm applies a grid-point search for a suitable $\Delta T_{LHmodel}$ profile)

1DVar The cloud operator H(**xb**)=0 therefore

$$J(\mathbf{x}) = \frac{1}{2}(-\mathbf{y})^T \mathbf{R}^{-1}(-\mathbf{y})$$

which does not depend anymore on the temperature and humidity profiles. The increments are null.

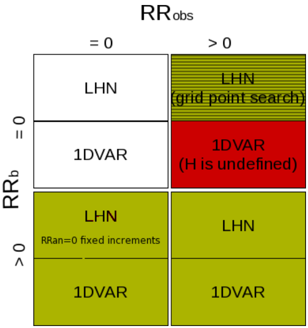
- $\mathrm{RR}_{obs} = 0$ and $\mathrm{RR}_b > 0$

LHN $\mathrm{RR}_{ana}= \beta\cdot \mathrm{RR}_{obs}+(1- \beta) \cdot \mathrm{RR}_b = 0$!! the de-crement is setto aa fixed ammount.

1DVar No problems! works very efficiently

- $\mathrm{RR}_{obs} > 0$ and $\mathrm{RR}_b > 0$ Each method plays its game !

When they work ok and ... when they don't!



- $\mathrm{RR}_{obs} = 0$ and $\mathrm{RR}_b = 0$ No winner, No looser!
- $\mathrm{RR}_{obs} > 0$ and $\mathrm{RR}_b = 0$

  LHN $\Delta T_{LHmodel} = 0$ there can't be an increment (the algorithm applies a grid-point search for a suitable $\Delta T_{LHmodel}$ profile)

  1DVar The cloud operator H(**xb**)=0 therefore

  $$J(\mathbf{x}) = \frac{1}{2}(-\mathbf{y})^T \mathbf{R}^{-1}(-\mathbf{y})$$

  which does not depend anymore on the temperature and humidity profiles. The increments are null.
- $\mathrm{RR}_{obs} = 0$ and $\mathrm{RR}_b > 0$

  LHN $\mathrm{RR}_{ana}= \beta\cdot \mathrm{RR}_{obs}+(1- \beta) \cdot \mathrm{RR}_b = 0$!! the de-crement is setto aa fixed ammount.

  1DVar No problems! works very efficiently
- $\mathrm{RR}_{obs} > 0$ and $\mathrm{RR}_b > 0$ Each method plays its game !

Radar data – RR derivation

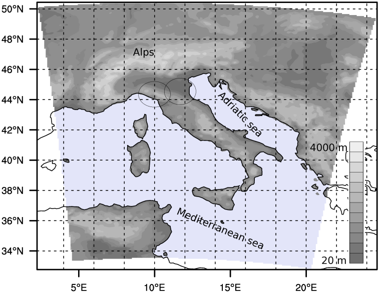


Figure: Integration domains for COSMO used in this study. The circles represent the spatial range (data coverage) of the two polarimetric radars used.

- Reflectivity converted in RR using Marshall-Palmer

$$Z = a\,R^b$$

with $a = 400$ and $b = 1.5$

- Error on RR_{obs} needed to calculate the **R** matrix following:

$$\epsilon = (1 - Q) + 0.2\left(\frac{\sigma}{\sigma_{max}}\right) Q$$

where:

- Q is a number in the range [0;1]; quality parameter
- σ sub-grid scale orography from a high resolution ($\sim$90 m) DEM

Radar data – RR derivation

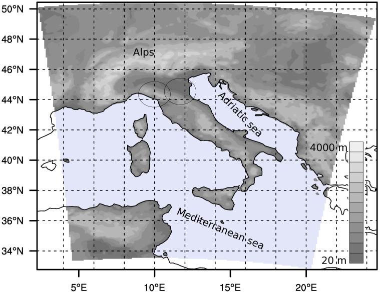


Figure: Integration domains for COSMO used in this study. The circles represent the spatial range (data coverage) of the two polarimetric radars used.

- Reflectivity converted in RR using Marshall-Palmer

$$Z = a\,R^{b}$$

with $a = 400$ and $b = 1.5$

- Error on RR_{obs} needed to calculate the **R** matrix following:

$$\epsilon = (1 - Q) + 0.2 \left(\frac{\sigma}{\sigma_{max}} \right) Q$$

where:

- Q is a number in the range [0;1]; quality parameter
- σ sub-grid scale orography from a high resolution ($\sim$90 m) DEM

Radar data – Data thinning

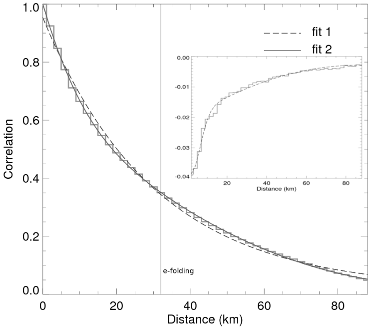


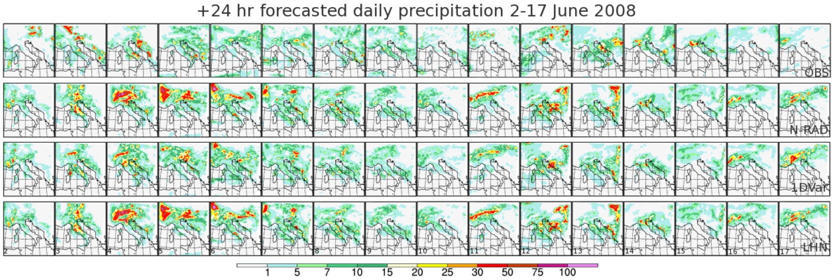
Figure: Auto-correlation field as a function of distance for the reflectivity fields. Two possible fitting function are displayed from which the e-folding distance is calculated; an exponential function $f(x) = a_0 e^{a_1 x}$ with least-square best fit parameters $a_0 = 0.87$ and $a_1 = -0.03$; and a non-linear function combination of a Gaussian and a quadratic function

$$f(x) = A_0 e^{-\frac{1}{2}\left(\frac{x - A_1}{A_2}\right)^2} + A_3 + A_4 x + A_5 x^2,$$ with parameters A_0=1.61, A_1=-33.18, A_2=18.56, A_3=0.68, A_4=-0.01 and A_5=5.6 10^{-5}. Small embedded picture: the derivative of the auto-correlation field.

High density observations with correlated errors can produce a degradation of the analysis because of the potential spreading of error in correlated neighbouring pixels

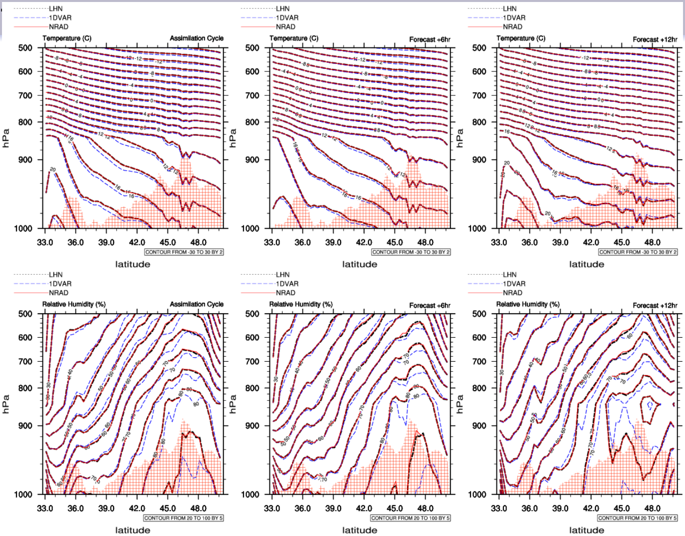
- temporal data thinning is simply performed by selecting data at a specific interval of 15 minutes
- the spatial sampling is determined by the decorrelation length of the reflectivity auto–correlation field

Synoptic Regime



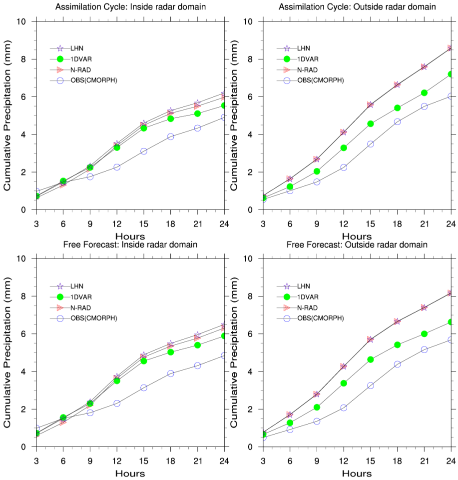
Sequence of the +24h forecast cumulative precipitation (mm/day)for the two assimilation experiments (LHN,1DVAR) the control (N-RAD) and has observed by the CMORPH dataset. Very heavy precipitation were predicted over the Eastern part of the Alps by the COSMO model in its operational configuration. The 4th and the 12th of June the prediction of severe thunderstorm caused the issued of two early warnings for heavy rains and consequent hydro-geological damage for those regions. The events were instead of minor intensity and afterwards classified as **false-alarm cases** by the civil protection authority.

Tempera



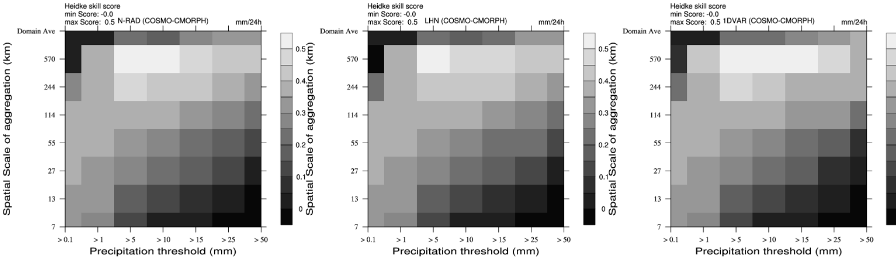
Zonal mean temperature and humidity fields. Analysis +6hrs,+12 hrs forecast fields are considered for a 18 day period starting from the 1st of June 2008. The zonal mean orography is reported on the bottom part of the figure. Important to notice is the change in the humidity field introduced by the 1DVAR

Cumulative Precipitation



3 hourly cumulative mean precipitation during the first 24-hour assimilation window and the first +24hr forecast range. Only points with RR $>$ 5 mmday are used.

Intensity-spatial scale RR verification

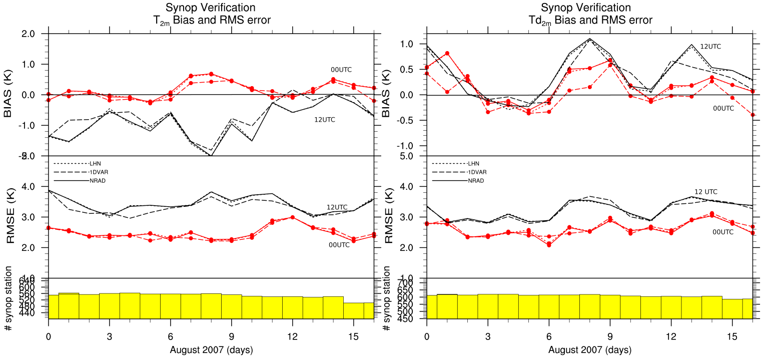


Heidke mean skill score as a function of the spatial scale of aggregation and the accumulation rain rate for the +24-h forecast.

$$HHS = \frac{\text{(hits+correct negative)-(expected correct)}_{persistence}}{\text{total event -(expected correct)}_{persistence}} \quad (3)$$

This score measures the fraction of correct forecasts **after eliminating those forecasts which would be correct due purely to the random chance**, here considered equivalent to the persistence (i.e. no change from previous forecast).

Surface variables



Bias and RMSE relative to the 2m dry and wet temperatures obtained for the 17 days considered, at 00 UTC (ANALYSIS) and at 12 UTC (+12 hr forecast). Last panel: total number of synop stations used in the comparison

Conclusions

1. For the 18 days of June 2008 taken as test period, the impact of RR assimilation is found beneficial for the forecast of RR amount in the first few hours of free forecast when using any of the two techniques.
2. Nevertheless, the 1Dvar showed to outperform the LHN in the capability to sustain in time the induced modification to the precipitation field.
3. The larger benefit in the forecast scores produced by the 1Dvar is mainly due to the capability of this method to provide to the nudging scheme vertical increments of temperature and humidity which are solution of a cloud scheme and therefore more dynamically consistent with the induced precipitation change
4. Intensity-scale verification showed that most of the benefit arising from the assimilation of radar derived rain rate is due to the improvement in the prediction of precipitation amount while the impact in the precipitation localization is of minor importance.

Conclusions

1. For the 18 days of June 2008 taken as test period, the impact of RR assimilation is found beneficial for the forecast of RR amount in the first few hours of free forecast when using any of the two techniques.
2. Nevertheless, the 1Dvar showed to outperform the LHN in the capability to sustain in time the induced modification to the precipitation field.
3. The larger benefit in the forecast scores produced by the 1Dvar is mainly due to the capability of this method to provide to the nudging scheme vertical increments of temperature and humidity which are solution of a cloud scheme and therefore more dynamically consistent with the induced precipitation change
4. Intensity-scale verification showed that most of the benefit arising from the assimilation of radar derived rain rate is due to the improvement in the prediction of precipitation amount while the impact in the precipitation localization is of minor importance.

Conclusions

1. For the 18 days of June 2008 taken as test period, the impact of RR assimilation is found beneficial for the forecast of RR amount in the first few hours of free forecast when using any of the two techniques.
2. Nevertheless, the 1Dvar showed to outperform the LHN in the capability to sustain in time the induced modification to the precipitation field.
3. The larger benefit in the forecast scores produced by the 1Dvar is mainly due to the capability of this method to provide to the nudging scheme vertical increments of temperature and humidity which are solution of a cloud scheme and therefore more dynamically consistent with the induced precipitation change
4. Intensity-scale verification showed that most of the benefit arising from the assimilation of radar derived rain rate is due to the improvement in the prediction of precipitation amount while the impact in the precipitation localization is of minor importance.

Conclusions

1. For the 18 days of June 2008 taken as test period, the impact of RR assimilation is found beneficial for the forecast of RR amount in the first few hours of free forecast when using any of the two techniques.
2. Nevertheless, the 1Dvar showed to outperform the LHN in the capability to sustain in time the induced modification to the precipitation field.
3. The larger benefit in the forecast scores produced by the 1Dvar is mainly due to the capability of this method to provide to the nudging scheme vertical increments of temperature and humidity which are solution of a cloud scheme and therefore more dynamically consistent with the induced precipitation change
4. Intensity-scale verification showed that most of the benefit arising from the assimilation of radar derived rain rate is due to the improvement in the prediction of precipitation amount while the impact in the precipitation localization is of minor importance.

One last thing ....

One last thing ....

До свидания церес два года..

One last thing ....

До свидания церес два года..

?

One last thing ....

До свидания церес два года..

?

See you in two years time...