Carpe Diem Area 1 overview – Data assimilation and NWP improvements

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1. NWP objectives of Carpe Diem
2. What is needed to improve precipitation forecasts in extreme weather events?
3. Data assimilation issues
4. Description and discussion of work packages (WP2 – WP5)
5. Planned and suggested collaboration

NWP objectives of Carpe Diem

- To focus on flood in small, medium and localised urban catchments ($100 - 5000$ $(km)^2$

- To improve the numerical prediction of rainfall (model grid resolution $\Delta x \approx 5 - 10$ km, forecast lead time 0 - 48 h).

- To assimilate radar doppler velocity (and spectral width) in both clear and precipitation filled atmosphere into NWP models.

What is needed to improve precipitation forecasts in severe weather events?

1. Basic forecasting approach

- Deterministic (traditional) NWP or probabilistic (ensemble) NWP?

- Global models and/or Synoptic scale LAM and/or storm scale LAM?

- Use of post-processing techniques (statistical down-scaling, Kalman-filtering) ?

2. Model resolution and model dynamics?

Depending on phenomena:

- Synoptic scale disturbances, $\Delta x \gtrapprox 10km$, hydrostatic equations
- Convective storms, $\Delta x \lessapprox 5km$, non-hydrostatic equations
- Orographic and coastline enhancements, $\Delta x \lessapprox 5km$, non-hydrostatic equations

Depending on catchment size:

- $\approx 10000(km)^2$, $\Delta x \gtrapprox 10km$ hydrostatic equations
- $\approx 100(km)^2$, $\Delta x \lessapprox 5km$ non-hydrostatic equations or possibly $\Delta x \gtrapprox 10km$ combined with post-processing

Something learnt from the TELFLOOD:

- Filtering of orography is needed to avoid spurious noise!

3. Model physical parameterizations

Parameterizations that are important for precipitation forecasts:

- Condensation and clouds, cloud microphysics (water phase, droplet spectra)

- Convection. Old convection schemes of *Kuo*-type, developed for grid resolution ≈ 100 km, are being replaced by mass flux schemes (e.g. Kain-Fritsch). At storm scale resolutions, explicit – resolved convection has to be taken into account.

- Surface and soil processes. A canopy layer and soil characteristics have to be introduced and variations of soil moisture become important. Detailed description of subgrid-scale variations of surface and soil characteristics (tiling) may need to be introduced.

- Vertical turbulent transports, i.e. the link between the surface fluxes and convection, condensation, clouds and precipitation, need to be improved. Explicit forecasting of TKE (Turbulent Kinetic Energy) is being introduced. Horizontal turbulent transports may need to be considered at storm-scale resolution.

4. Initial data needs

The following initial data variables may be considered high priority:

- Vertical profiles of atmospheric wind, water vapour and temperature. In accordance with geostrophic adjustment theory, wind is considered more important than temperature at high horizontal resolution.
- Surface pressure
- Soil and surface conditions, in particular soil moisture.
- Atmospheric aerosoles.

Cloud variables are more difficult to assimilate but may become increasingly important when assimilation techniques improve and when cloud parameterization schemes become more realistic.

5. Observations

Traditional observations:

- Radiosonde (temperature, wind, water vapour and surface pressure)
- SYNOP, SHIP and DRIBU (surface only)
- Aircraft reports (wind and temperature)

Radar observations:

- Radial wind vectors, VAD profiles
- Reflectivity $\approx$ 3D precipitation intensity (latent heating)

Satellite observations:

- Satellite sounding data, e.g. TOVS (temperature and humidity profiles, precipitation)
- Cloud drift winds
- Scatterometer data (10 meter winds)
- Imager data (clouds, surface conditions)
- Ground-based GPS data (integrated water vapour)

6. Data assimilation techniques

Various data assimilation techniques exist. It is not clear what will be the the best solution for real-time high resolution precipitation forecasting. Several techniques will be compared within Carpe Diem:

- Variational data assimilation, 3D-Var and 4D-Var.
- Continious assimilation with nudging.
- Use of output from standalone mesoscale objective analysis schemes.

Variational data assimilation - formulation

Problems and critical issues are common to most data assimilation techniques. We will briefly discuss these within the framework of **variational data asimilation**. We will first give a brief definition of the basic variational data assimilation problem.

Minimize

$$J = J_b + J_o + J_c =$$

$$(x(t_0) - x_b(t_0))^T B^{-1} (x(t_0) - x_b(t_0)) +$$

$$(Y(t) - Hx(t))^T R^{-1} (Y(t) - Hx(t)) + J_c$$

over a time period $t_0 \leq t \leq t_1$ where

J_b measures the distance between the model initial state vector $x(t_0)$ and a model background state vector $x_b(t_0)$, for example a short range forecast.

J_o measures the distance between the model state $x(t)$ and available observations $Y(t)$ from the time-period. The model state $x(t)$ is obtained through integration of the NWP forecast model M from the initial time t_0, $x(t) = M(x(t_0))$.

J_c is included to prevent un-realistic high frequency oscillations (gravity wave contraint).

B is a matrix containing the covariances of the background model state errors, R is the matrix of the covariances of the observation errors and H is the observation operator projecting the model state vector on the observed quantities.

Variational data assimilation - critical issues

- Variational data assimilation schemes are often developed with 4D-Var as the ultimate goal. 3D-Var is a natural step towards 4D-Var. 4D-Var has not yet proven to be affordable and cost-efficient for short-range mesoscale NWP applications.

- 3D-Var and, in particular, 4D-Var are often applied in their incremental form. This means that the assimilation increment $\delta x = x - x_b$ is applied at a coarser spatial resolution than the model background x_b. Furthermore, a tangent-linear model may be applied for the forecast of the assimilation increment over the time period of the assimilation, and a tangent-linear observation operator may be applied to the assimilation increment, while the full non-linear forecast model and the full non-linear observation operator are applied to the model background field in full spatial resolution. The incremental approach makes the computational task more tractable.

- Important forecast model non-linearities, in particular with regard to physical processes at high resolution in space and time, may prohibit the use of the incremental approach and make application of 4D-Var less tractable.

- Important non-linearities in the observation operators, for example those for satellite radiance data, may necessitate the application of several ”outer loops” with the full non-linear observation operators during the minimization.

- A basic limitation of 4D-Var is the intrinsic assumption of a perfect forecast model.

- The huge dimension of the background error covariance matrix B necessitates introduction of simplifications, that may obstruct the efficiency of 3-4D-Var in comparison with more simplified and localised assimilation techniques. Common simplifications of B include assumption of homogeneity and isotropy with regard to spatial correlations and near-geostrophy. Attepts to include flow-dependency in B have so far had very limited success. (The present project will include an attept for online estimation of the diagonal of B – the background error variances.

- High-resolution data, like radar data and satellite image data, need to be pre-processed to ”super-observations” or to be spatially thinned. Pre-processing may include a gross error check, e.g. by comparison with the background field. The variational assimilation may include a variational quality control, taking account of non-Gaussian observation errors.

- The observation error covariance matrix is often assumed to be a diagonal matrix, thus observation errors are assumed to be un-correlated. This is likely to be less valid for remote sensing data.

- It is a general experience that remote sensing observations often have to be modified by bias correction schemes.

- It is preferrable that assimilation control variables have Gaussian statistical distributions. Various transforms may be applied, e.g. for the moisture variable, to come closer to Gaussian distributions.

- Pre-conditioning is important to get a faster convergence of the minimization. A first attempt can be to diagonalize the background error covariance matrix B by an appropriate transformation of the model state vector.

- Application of a digital filter as a weak constraint has recently had some success in minimizing fast model oscillations and model spin-up.

Work Package 2: Extraction of information from Doppler winds

- SMHI will develope a pre-processing of Doppler wind data to "super-observations". The pre-processing will include ambiguity removal and 3D volume averages of radial winds, retaining characteristics of the original polar data, and error estimation.

- University of Essex and ARPA/SMR will derive both componehts of the wind field from overlapping radars (relaxation of the homogeneity assumption of VAD).

- DLR will examine clear air radar echoes for obtaining wind profiles and boundary layer characteristics.

Work Package 3: Data Assimilation

- SMHI and FMI will develope observation operators for radar radial winds in 3D-Var and 4D-Var. The model wind profile will be projected on the radial winds and the corresponding tangent-linear and adjoint operators will also be developed. To avoid problems with influence from observed vertical velocities, low elevation radar angles will be treated first. Quality control algorithms will be developed and observation error statistics will be estimated. Data impact studies will be carried out.

- University of Barcelona will apply continuous data asimilation and nudging for radar, satellite and conventional observations.

Work Package 4: Assessment of NWP model uncertainty including model errors.

- PROGEA, in collaboration with SMHI and University of Barcelona, will set up a Kalman filter approach based upon optimality conditions in terms of independence in time of the innovation process (IIP) and compare it with results from the Maximum Likelihood/Simplified Kalman Filter (ML/SKF) approach.

- SMHI will investigate the possibilities for online estimation of forecast error standard deviations (by ML/SKF of KF techniques) to be used within the framework of variational data assimilation.

Work Package 5: Assessment of improvements in NWP

- ARPA/SMR and CNR/ISAO will identify and examine severe weather cases and study the impact of remote sensing data for these cases.

- ARPA/SMR will develope and test a Very Short-range Forecasting (VSRF) system. A mesoscale analysis (LAPS) will be linked to the (ETA) model. The impact of remote sensing data will be studied.

- CNR/ISAO will introduce satellite radiance data to the mesoscale analysis: Meteosat, NOAA AVHRR, ATOVS and MSG data. Cloud droplet effective radius, cloud ice content, rainfall estimates and mesoscale organization will be studied.

Planned collaboration within Area 1:

- U. Essex and ARPA/SMR will collaborate on dual doppler wind retrieval. (WP2)
- SMHI and FMI will develope variational assimilation of radar radial winds together. (WP3)
- PROGEA, SMHI and U. Barcelona will collaborate on model error assessment. (WP4)
- ARPA/SMR and CNR/ISAO will collaborate on mesoscale analysis. (WP5)

Suggested further collaboration:

- Comparison of standalone dual doppler retrieval (WP2) with variational assimilation from overlapping radars (WP3).
- Comaparison of 3D-Var/4D-Var (WP3), nudging (WP3) and VSFR (WP5) on a common severe weather case (WP5).
- Assessment of the impact of radar data on the results of the total model chain ((Radar→NWP) → (Radar → Flood model)) (Area 1, 2 and 3)
- Assessment of the combined effect of several types of remote sensing data, e.g. AMSU-B moisture, GPS moisture, MODIS moisture and Soil moisture assimilation. Interaction with other EU projects for this purpose.