Priority Program SPP 1167 of the DFG

Quantitative Precipitation Forecast

Studies of the Process Chain and the Predictability of Precipitation with the D-PHASE Ensemble and COPS Observations

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COPS 4D data set

- 18 IOPs during 35 days
- Combination of various forcing mechanisms
- Several extreme events captured
- Unique sensor synergy with excellent data quality
- Precipitation process chain can be studied in detail
- All COPS science questions can be addressed

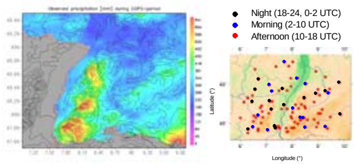


Fig.1: Precipitation and MSG CI statistics during COPS

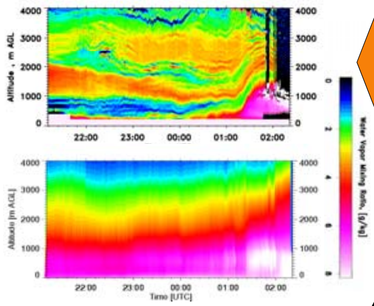


Fig.3: IPM DIAL and IMAA microwave radiometer water-vapor measurement during IOP 13, August 1-2, 2007.

Fig.2: Easy access to information concerning missions and quicklooks via COPS web site.

COPS-GOP-D-PHASE data archive

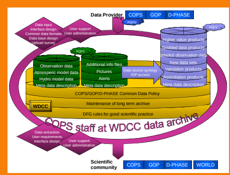
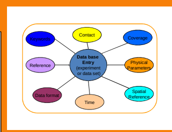


Fig.4: Data management tasks.



Comprehensive meta data description is crucial for long-term archiving

Suitable access points are defined for each data set time series

Fig.5: WDCC data base design.

D-PHASE ensemble

- Unique multi-model combination using different parameterizations, data assimilation systems, and boundary conditions:
  - 6 ensemble forecast systems
  - 11 models with convection parameterization
  - 9 convection permitting models
- Suitable for selection of multi-model ensemble and for predictability studies

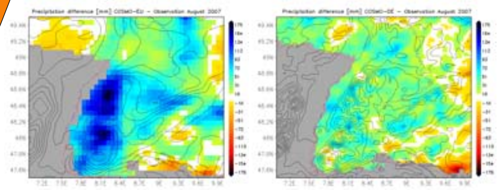


Fig.6: D-PHASE model evaluation using COSMO-EU with convection parameterization and convection permitting COSMO-DE gives already insight in one key error of precipitation forecasting in complex terrain: the windward-lee effect. Obviously, strong systematic errors are caused by convection parameterization.

IPM Project Office

First case study of process chain, IOP 8b

Deep convection with short lifetime was initiated in the COPS domain.

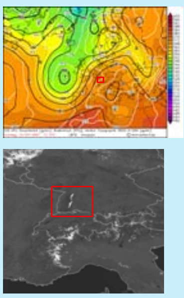


Fig.7: Large-scale conditions: GFS analysis and MSG RSS

A. Convection initiation

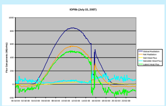


Fig.8: Surface fluxes at Supersite S.

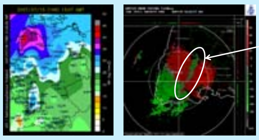


Fig.9: GPS IWV field and radar radial velocity.

B. Organization of convection and microphysics

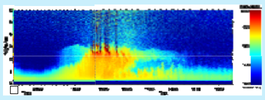


Fig.10: ABL evolution at Supersite M.

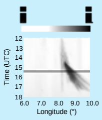


Fig.11: MSG IR 10.8-μm BT Hovmüller diagram.

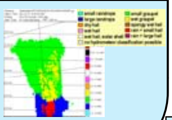


Fig.12: Poldirad RHI scan.

Model performance during IOP 8b

Just two models (MESO-NH and AROME) managed to simulate deep convection.

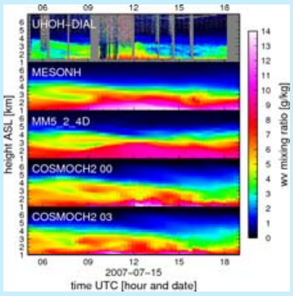


Fig.13: Model water-vapor meteograms at Supersite H in comparison with DIAL observation.

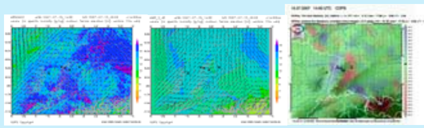


Fig. 14: MESO-NH, MM5 simulation (with cloud liquid water) and VERA analysis valid for 14 UTC. Pronounced moisture flux convergence is observed over the Black Forest.

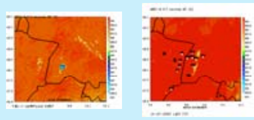


Fig.15: Convection simulated in MESO-NH in comparison with observation by means of MSG BT.

Proposals of suitable combinations of model forecasts for process studies in order to:

Evaluate the impact of different data assimilation systems and observations.
First results: Strong deviation between model initial fields and observations with respect to water-vapor.

Investigate the initiation and organization of convection.
First results: Flow in complex terrain, water-vapor field, and temperature structure must be studied in great detail with COPS data set.

Analyze failures of parameterizations and evaluate model physics.
First results: Convection parameterization responsible for systematic errors but deficiencies remain in convection permitting models.

Analyze and improve model ensemble skills for optimal combination of ensemble

- Ensemble calibration using, e.g., Bayesian averaging or reforecasting.
- Performance analyses with probabilistic skill scores
- Selection of multi-boundary, convection permitting multi-model ensemble

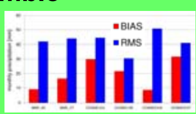


Fig.16: First evaluation of D-PHASE models in COPS domain.

Studies of predictability based on Bayesian statistics with NUMEX

Bayesian factor B: $B_{ir} = \frac{l(\vec{d} \mid M_i)}{l(\vec{d} \mid M_r)}$ l: likelihood, d: data vector, M_i: ith model, M_r: reference model.

If the variable is multivariate normally distributed $l(\vec{d} \mid M_i) = \frac{1}{\sqrt{(2\pi)^q}} \sqrt{\frac{\det \mathbf{G}_i^{-1}}{\det \mathbf{K}_i \det \mathbf{K}_0}} \exp\left(-\frac{1}{2}\Lambda_i\right)$

with $G_i = K_i^{-1} + K_0^{-1}$ and $\Lambda_i = (\vec{d} - \vec{f}_i)^T \mathbf{K}_0^{-1} \mathbf{G}_i^{-1} \mathbf{K}_i^{-1} (\vec{d} - \vec{f}_i)$

A variable d is predictable in dependence of forecast range τ if $P_r(d) := B_{ir}(d) > B_c$ (sign. nonzero).
Consequently, we are proposing a method to quantify predictability of, e.g., precipitation, in dependence of forecast range, resolution, domain, and model physics.

Extension of the results from the COPS to the D-PHASE domain. Contributions to WWRP, such as THORPEX and the international Data Assimilation Testbed.