Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Generation of an Object-based Nowcasting Ensemble

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SINFONY

Contents

KONRAD3D (KONvektive Entwicklung in RADarprodukten)

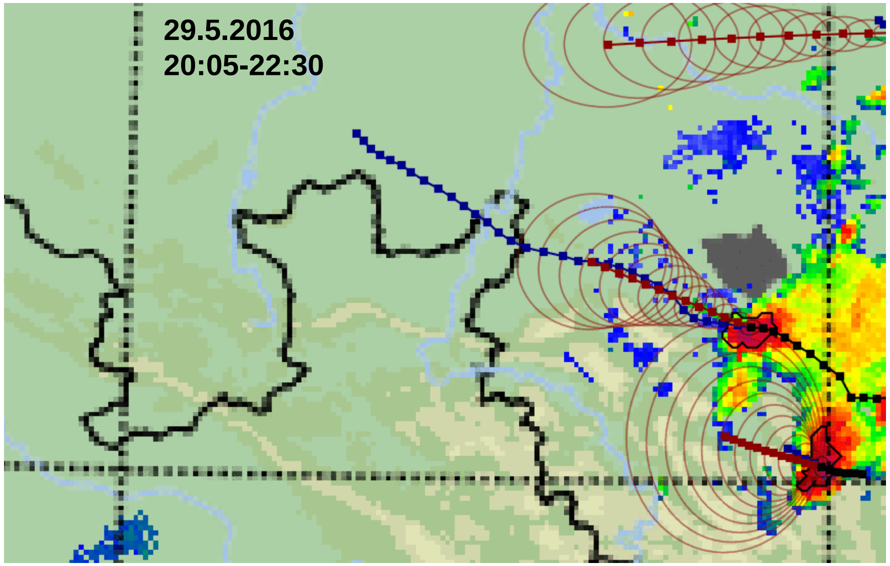
- Object detection, tracking and forecasting system
- In-house development by Manuel Werner (Poster 19)
- Entering test phase soon
- Implemented in POLARA framework
- Will replace legacy system KONRAD

KONRAD3D

POLARA Polarimetric Radar Algorithms

Features

- Based on 3D quality-assured radar data
- Adaptive thresholding
- Kalman filtering of cell-centroid position



previous,
predicted and
subsequent cell-centroid positions

Mode of Operation and Limitations

- Cell detection in sweeps and 2D projection
- Cell heading from optical-flow method and cell-centroid relocation
- No account for changes in heading or evolution

Goal

➔ Correct representation of nowcasting uncertainties

Major Uncertainties

➔ Detection method and its parameters, esp. detection thresholds

➔ Tracking and forecasting method, especially process model and noise assumption

➔ Cell evolution

Possible Approaches

➔ Probabilistic system:

- ➔ Harness techniques with pure probabilistic output, e.g. Kalman Filter

➔ Ensemble system:

- ➔ Generate ensemble of forecasts through perturbation or variation

Kalman-Filter Principle

- ➔ Modelling of stochastic process in state space as Markov chain
- ➔ Iterative Bayesian combination of prediction and measurement to an analysis, which is more accurate than the combination ingredients
- ➔ Prerequisite:
  - ➔ Linear process model,
  - ➔ Gaussian process and measurement noise,
  - ➔ Few measurements and state variables

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One-dimensional example: position tracking

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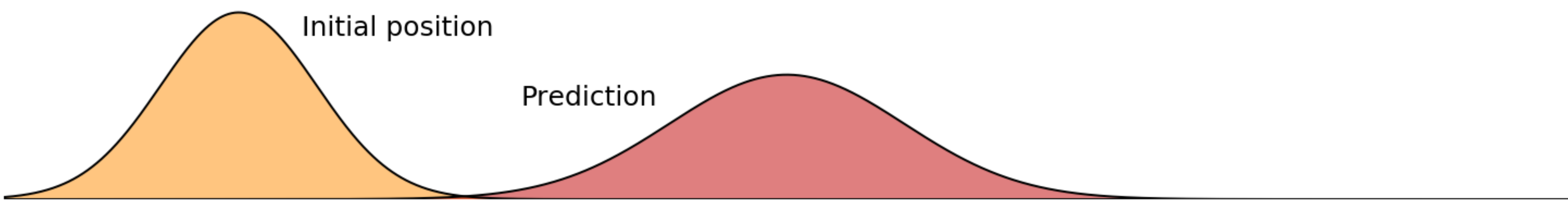

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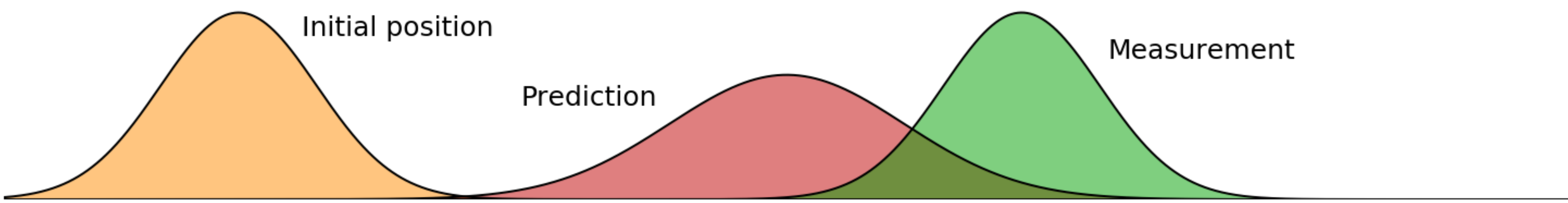

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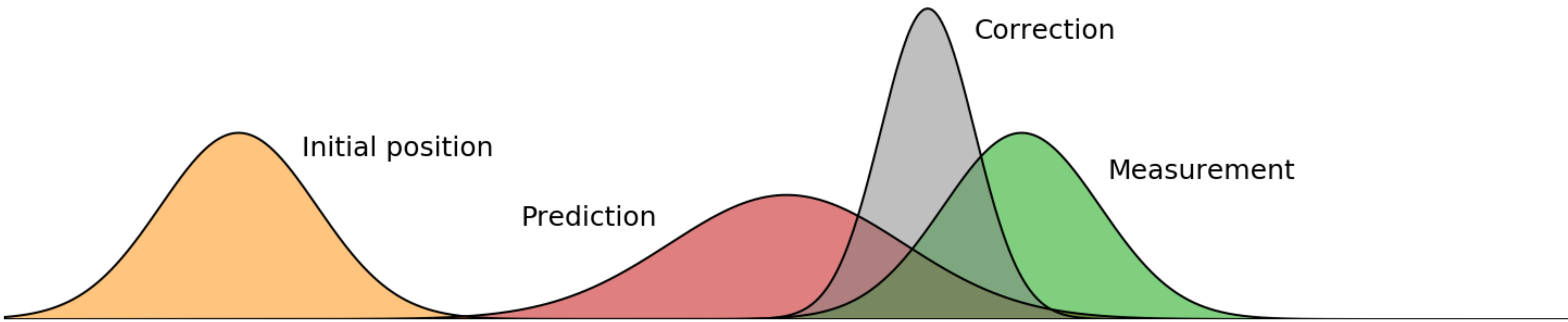

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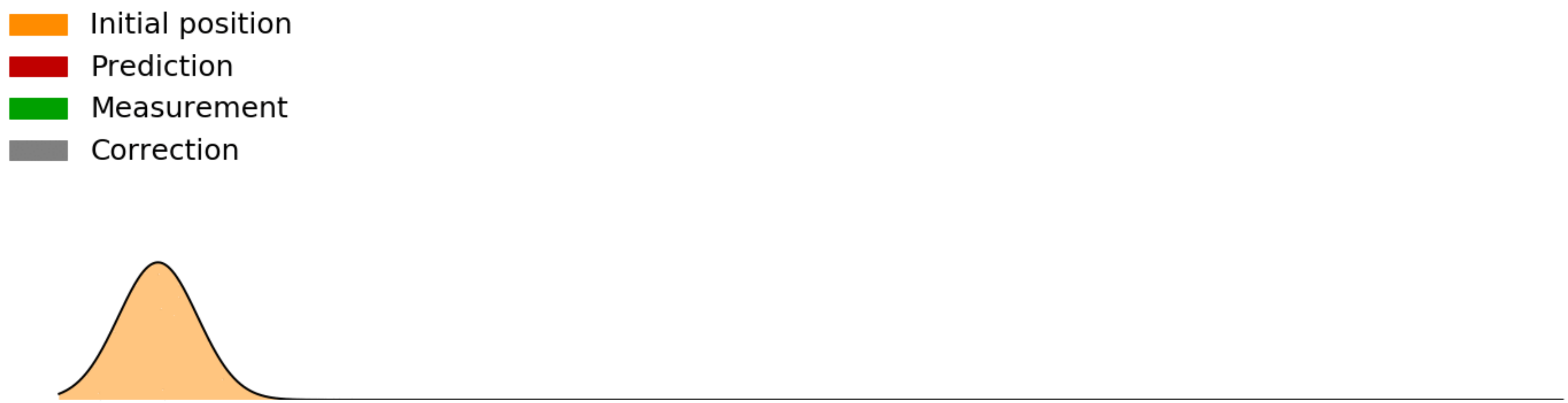
One-dimensional example with measurements



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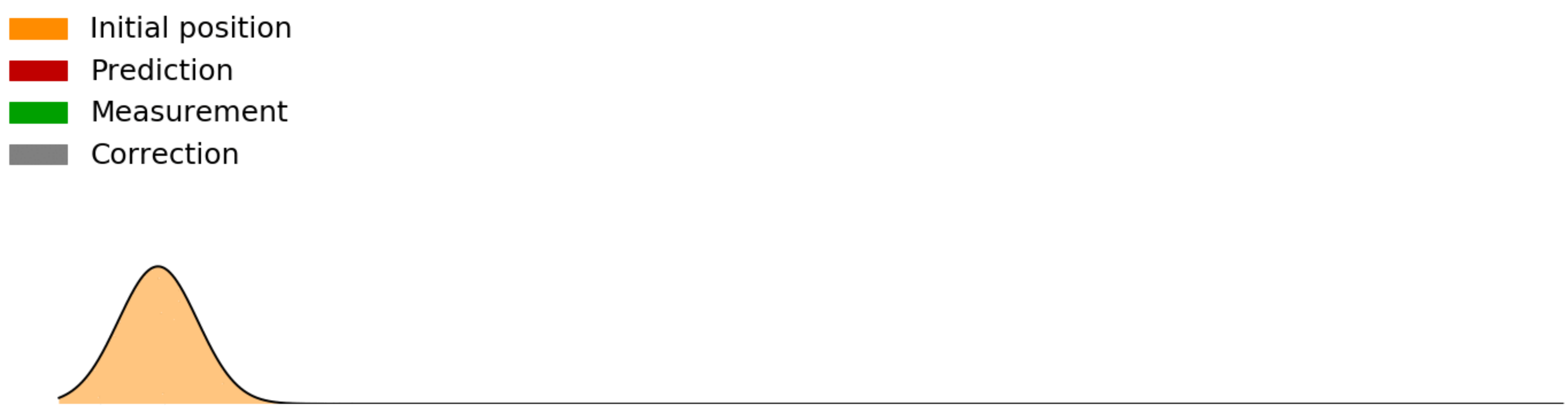
One-dimensional example without measurements



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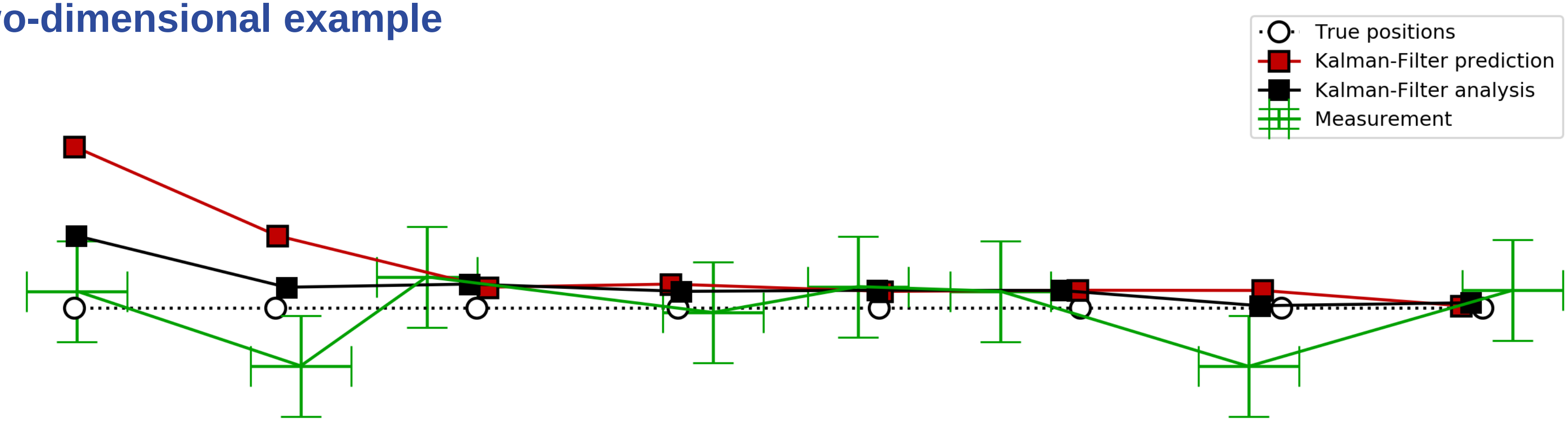
Two-dimensional example



Kalman Filter in KONRAD3D

Process Model

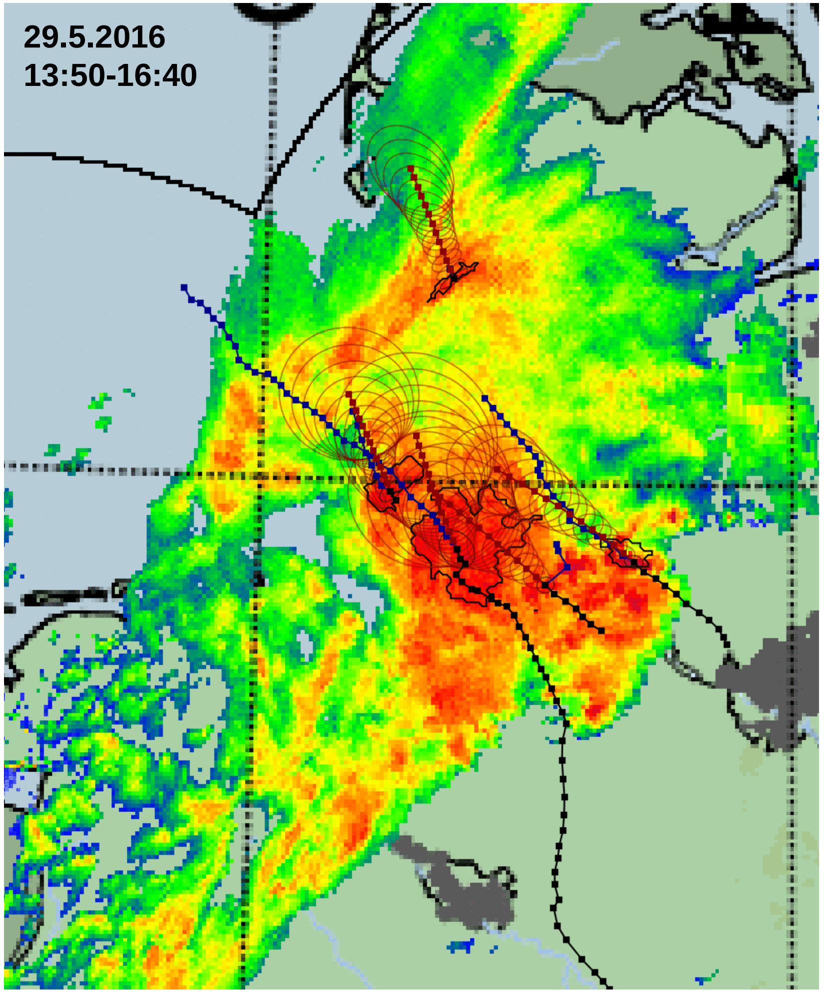
- Kalman filtering of the 2D-projected cell centroid (3D dBZ-weighted cell mean)
- Constant acceleration model: forecasting of curved tracks possible

Measurement

- Measurement error as covariance of the dBZ-weighted cell mean
- Optical-flow motion vectors only as first guess of the velocity of newly detected cells

Presentation

- 60-min forecast in 5-min steps
- Uncertainty ellipse for analysis (previous in black, subsequent in blue) and forecast (red)



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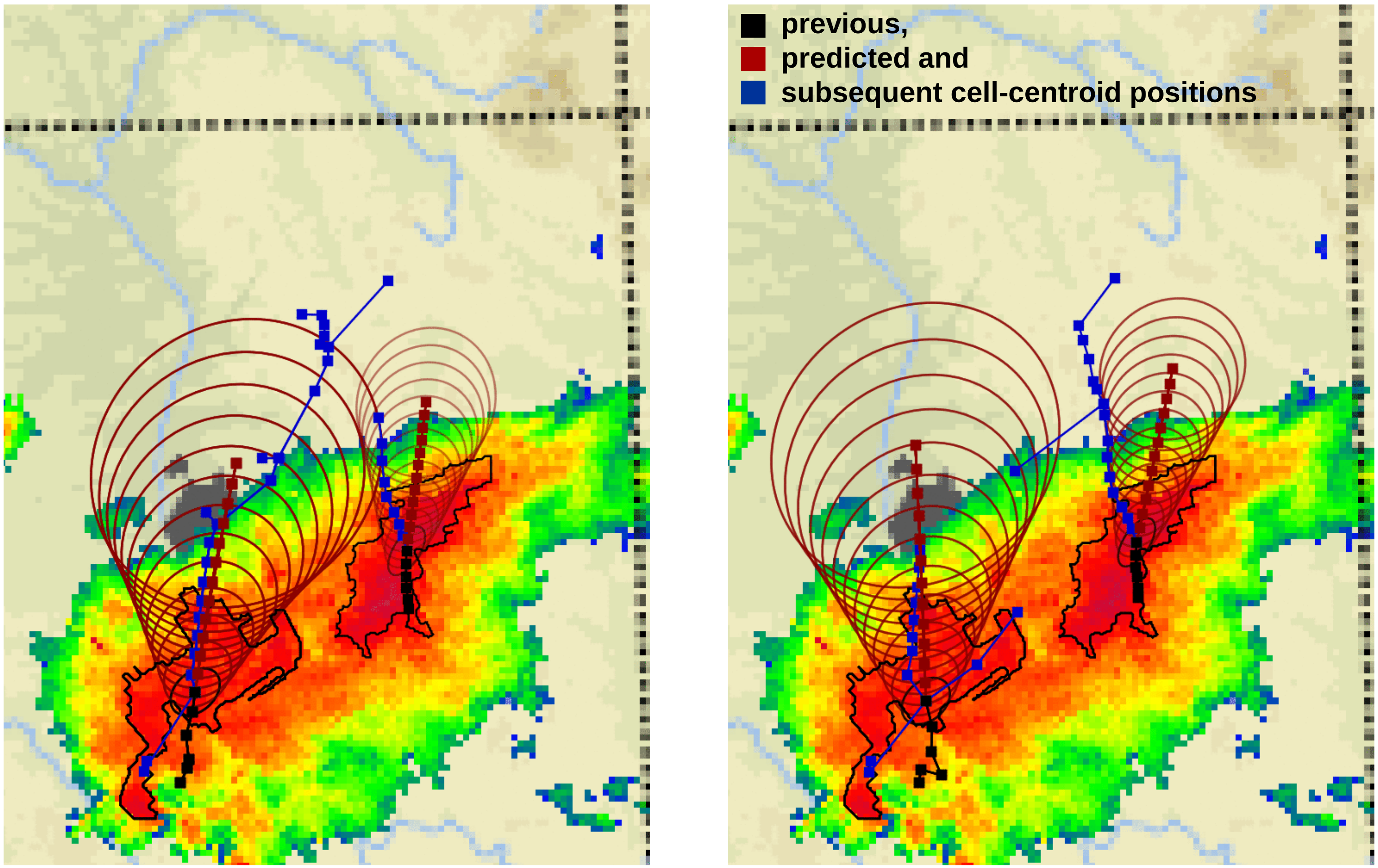
Motivation



KONRAD3D ensemble members using different detection thresholds (29.5.2016 6:50-8:15)

Motivation

Shortcomings of Pure Probabilistic Approach

- ➔ Uncertainties due to range of suitable method parameters only through additional noise
- ➔ Cell evolution as non-linear function cannot be implemented in basic Kalman filter
- ➔ Error ellipse as uncertainty of cell centroid position difficult to understand

Advantages of Ensemble Approach

- ➔ Uncertainties from parameter variation can be captured by an ensemble of detection and tracking runs with different settings
- ➔ Cell evolution as non-linear function can be implemented in Ensemble Kalman filter
- ➔ Ensemble members as cell realizations easy to understand and reason about

Concept

Cell Detection

- Runs of KONRAD3D detections from variations of algorithm parameters (thresholds and Kalman filter noise) to capture the parameter uncertainty
- Clustering of detected KONRAD3D cells
- Cell cluster centroid and its variance from mean and variance of single detections

Ensemble Generation

- Stochastic ensemble generation for every cell cluster
- Application of Ensemble Transform Kalman Filters:
  - Currently constant velocity model for cell cluster centroid motion
  - KONRAD3D cell cluster used as measurement

Cell Life Cycle

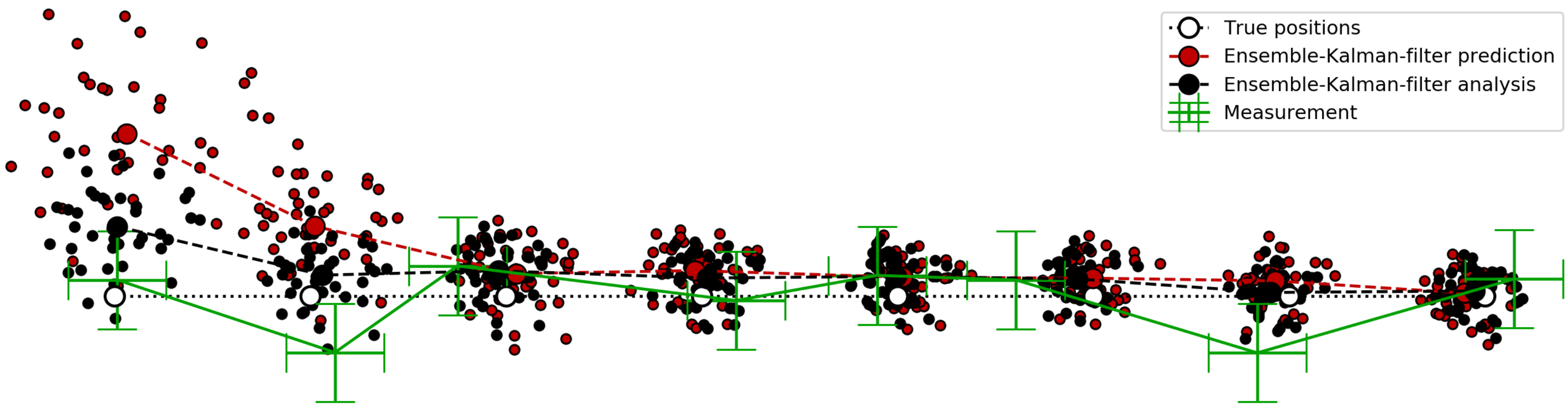
- Cell life cycle as parabola shape opening down for cell area over cell age
- Cell life time and maximum cell area as parabola parameters are Monte-Carlo generated for ensemble members

Ensemble Kalman Filter

Properties

- ➔ Kalman-Filter works directly on Gaussian distributions, while Ensemble Kalman Filter (EnKF) works on samples, i.e., ensemble members
- ➔ EnKF turns into Kalman-Filter for large number of members
- ➔ EnKF avoids expensive matrix inversion
- ➔ EnKF is robust against non-linearities and thus deviations from Gaussian distributions (alternatively Extended Kalman Filter)

Example: Ensemble Kalman Filter



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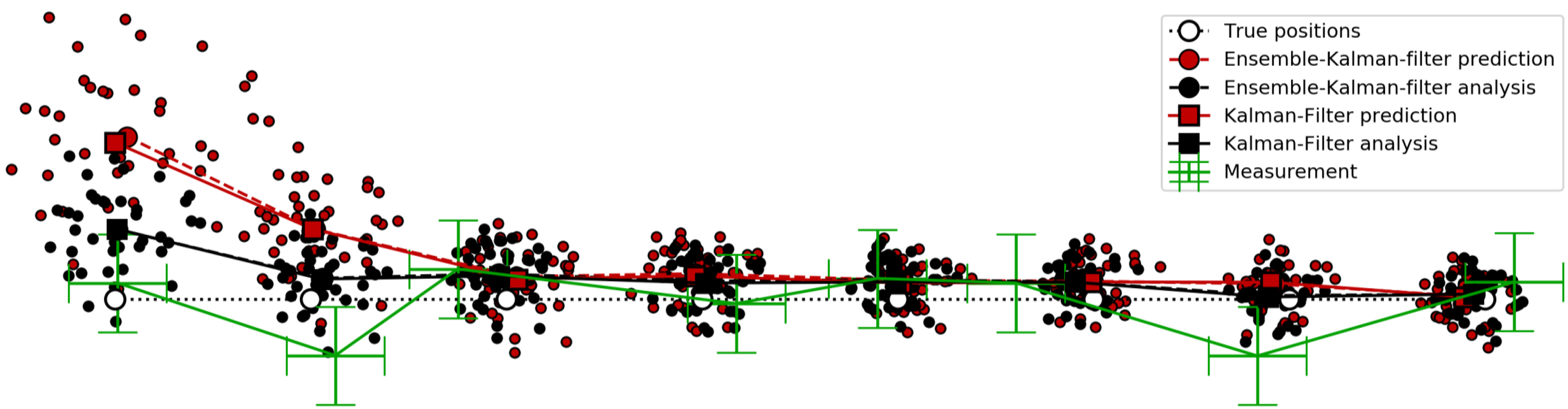
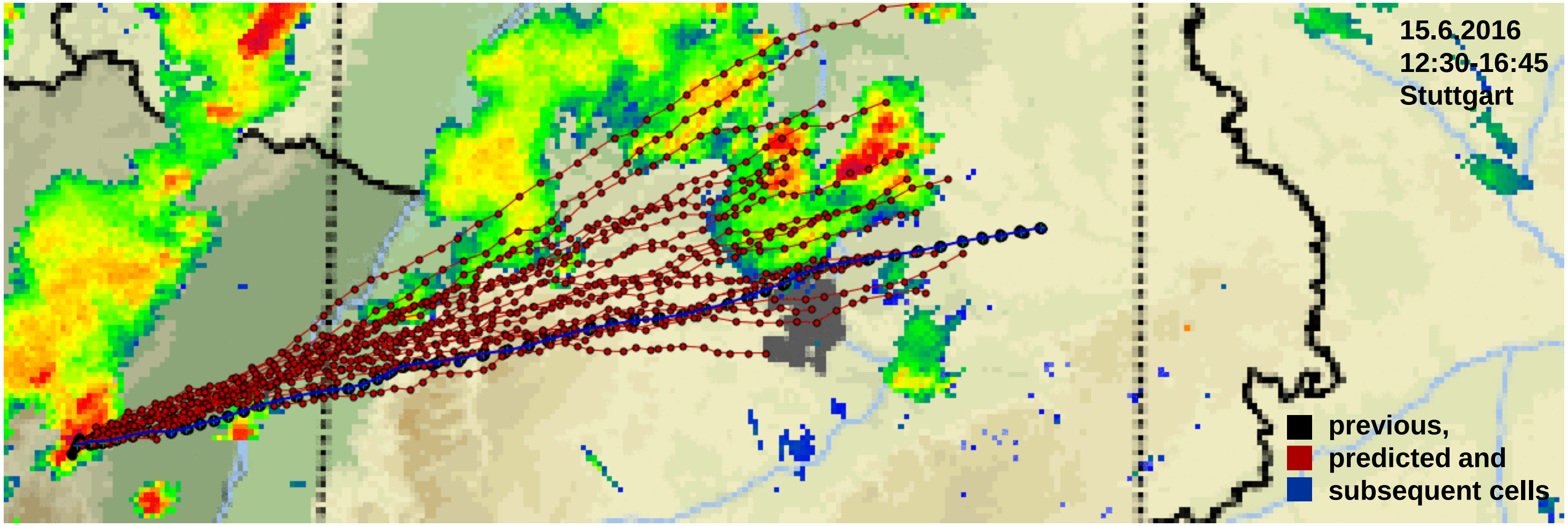
Example: Ensemble Kalman Filter vs. Kalman Filter

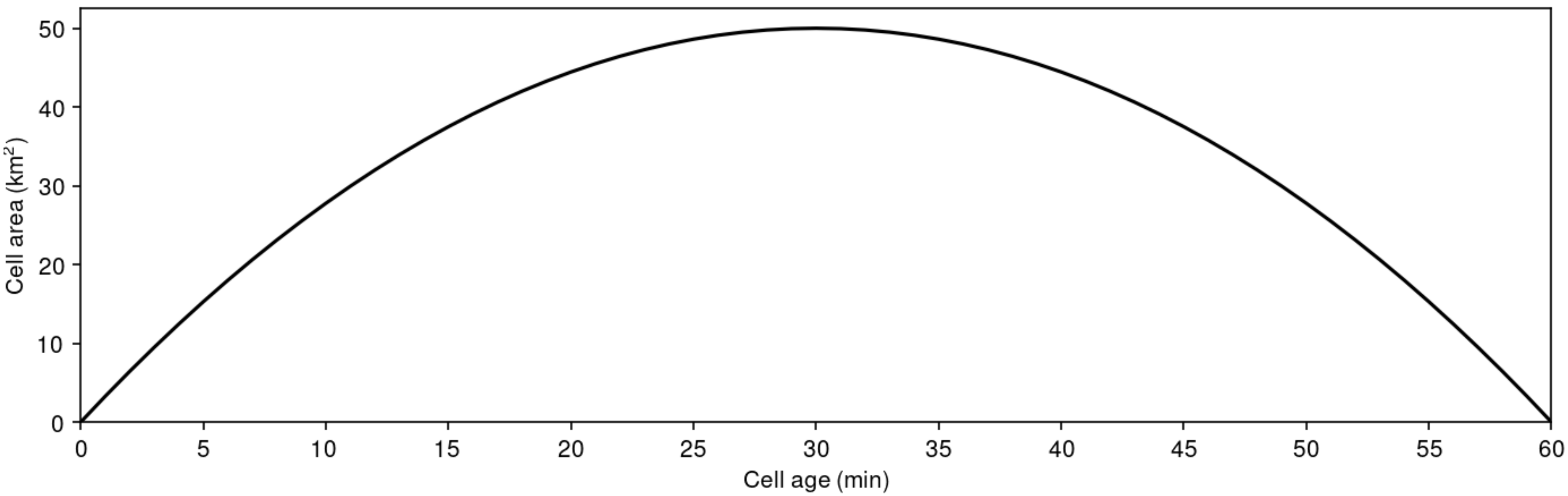


Example Ensemble

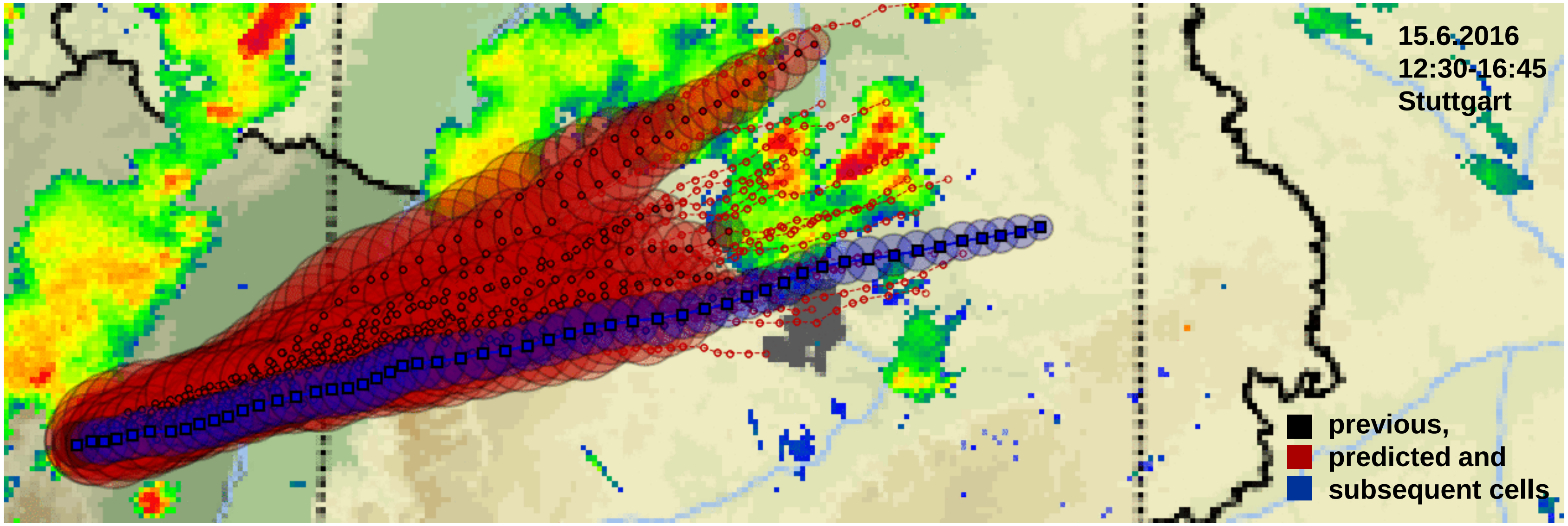


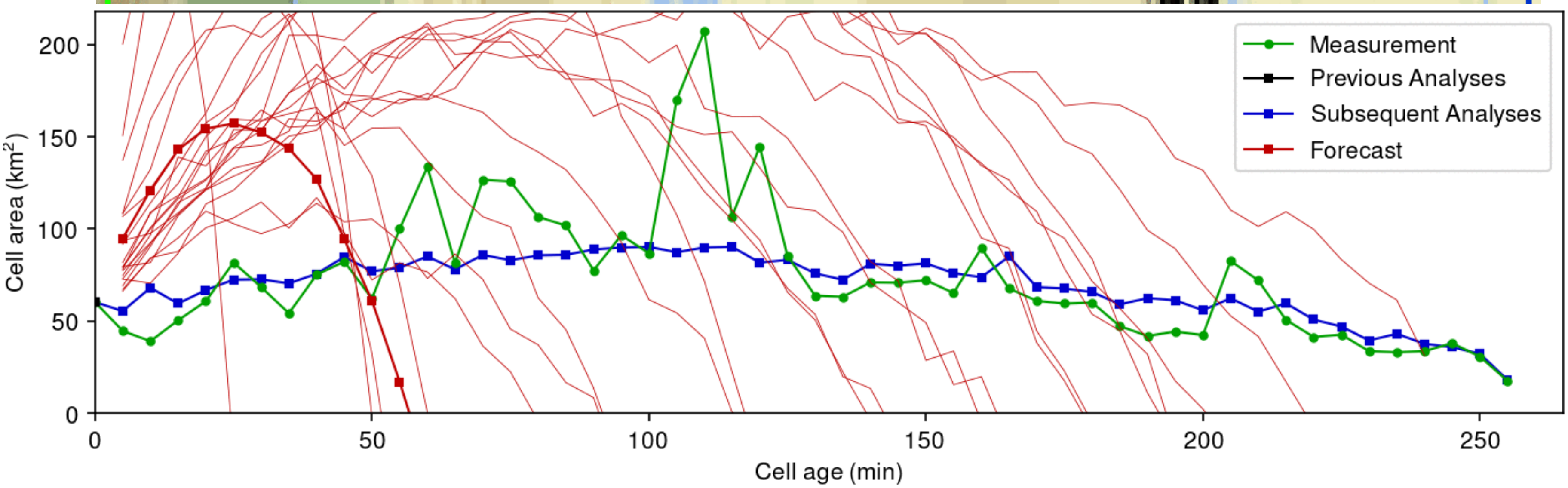
Implementation Cell Life-Cycle

- Ansatz from life-cycle analysis by Kathrin Wapler (Poster 3):
  Cell area a versus cell age t as parabola opening down:
  $$a(t) = -\frac{4a_{\max}}{\tau^2}\left(t - \frac{\tau}{2}\right)^2 + a_{\max}$$
  with lifetime τ and maximum cell area $a_{\max}$.
- KONRAD3D only measures cell area
- Lifetime τ and maximum area $a_{\max}$ sampled from large variance Gaussian distribution



Prototype Object-based Nowcasting Ensemble





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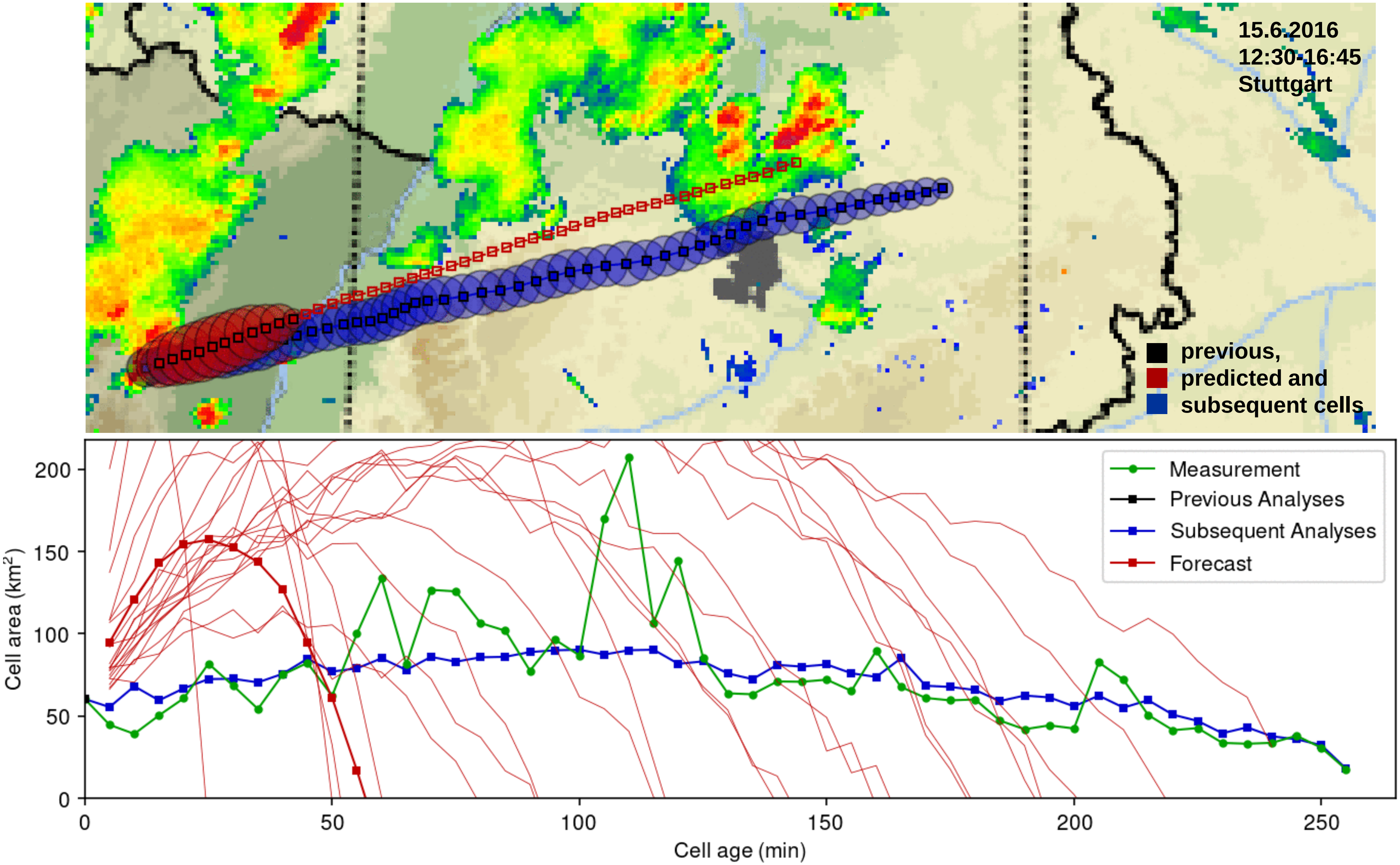

Summary

Probabilistic Nowcasting with Kalman Filter

- ➔ KONRAD3D extended by Kalman filter,
- ➔ Cell centroid forecast with uncertainty ellipse

Prototyp Object-based Nowcasting Ensemble

- ➔ KONRAD3D detection with variation of thresholds and Kalman-filter noise
- ➔ Clustering of detections and sample ensemble from cluster mean and variance
- ➔ Ensemble Kalman filter applied to cluster
- ➔ Implementation of cell evolution as down-facing parabola for cell-area time series

Outlook

- ➔ Consider other properties for life-cycle modeling than cell size
- ➔ Improve handling of cell splits and merges
- ➔ Tuning and Verification of prototype
- ➔ Implementation of prototype in C++ framework POLARA

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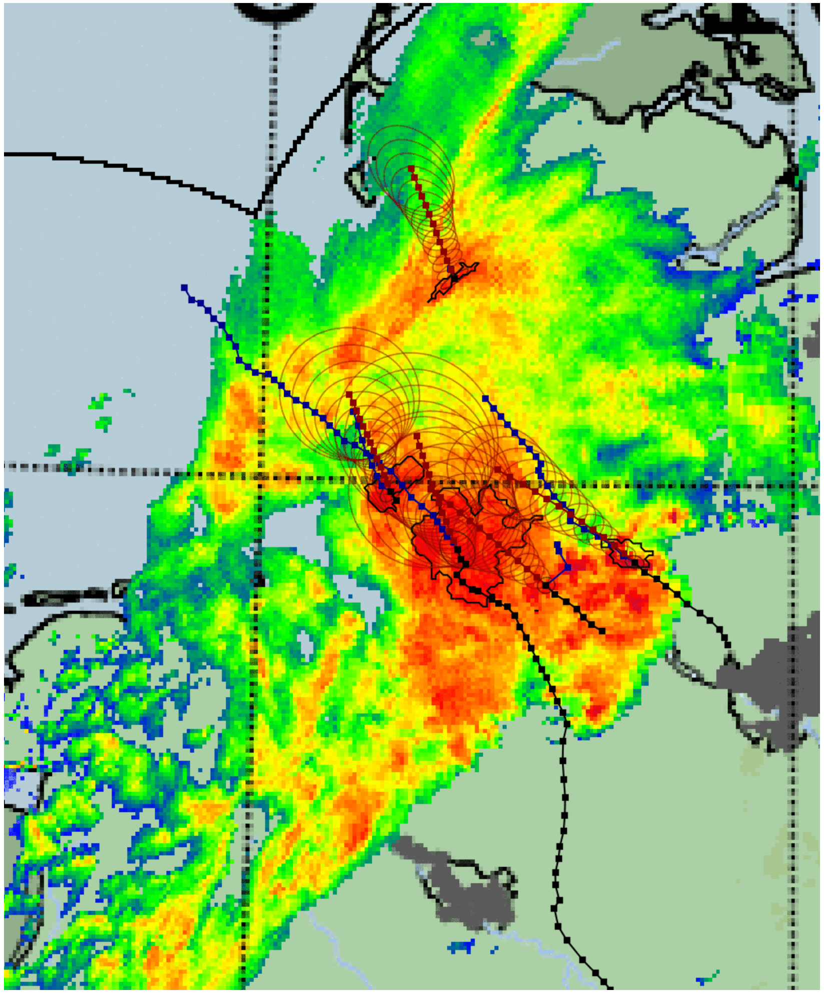

Backup

Ensemble Generation

Uncertainties in Nowcast Predictions

Measured Data

- Weather radars yield a spatially smoothed, indirect and time-singular image
- Positioning and intensity errors, jamming and artefacts

Method

- Uncertainty in object identification: used properties, thresholds, method
- Tracking and forecast uncertainties: e.g. predecessor−successor matching
- (No) modeling of physical processes

Uncertainties in Nowcast Predictions

Measured Data

- Measurement Principle
- Measurement Error

Method

- Object Identification
- Tracking and Prediction
- Process Model

Ensemble Generation

Uncertainties in Nowcast Predictions

Measured Data

- Measurement Principle
- Measurement Error

Method

- Object Identification
- Tracking and Prediction
- Process Model

Ensemble-Generation Approaches

Data Perturbation

➔ Stochastical perturbation of data, e.g. though noise analysis

Method and Parameter Variation

➔ Optical-Flow algorithm for the computation of motion vectors: e.g. method, thresholds, smoothing

➔ KONRAD3D: e.g. methods, thresholds, predecessor matching, Kalman-filter parameters

NWP Information

➔ Motion vectors averaged from observation and NWP ensemble

➔ Cell evolution from NWP ensemble

Dynamics

➔ Cell evolution from results of life-cycle analysis (Kathrin Wapler)

Ensemble Generation

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