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Redefining decision making: introducing probabilistic forecast products to aviation applications

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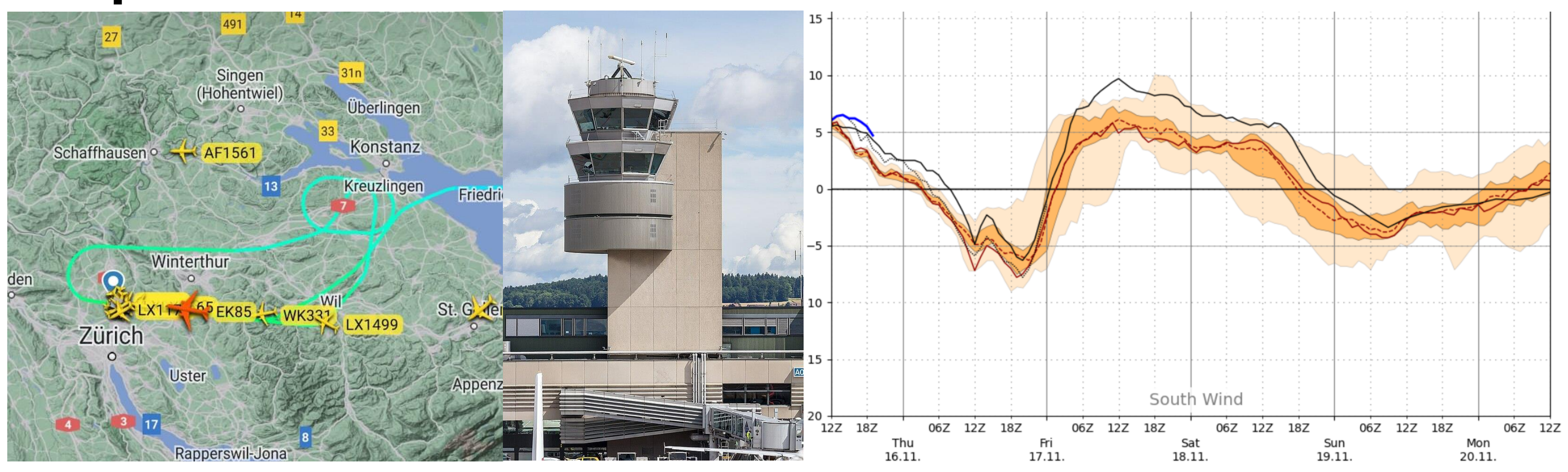
The Goal: More probabilistic forecasts for our aviation weather products

There is no aviation operations without secure weather information. Efficient and safe air traffic management relies on accurate meteorological predictions on different timescales from nowcasting to the midrange. On top of that, it is crucial to enable a safe interpretation of uncertain weather data so that these forecasts are fruitful for planning and decision making within aircraft operations.
In the project AVIA26 we combine machine-learned, probabilistic forecasts of wind, visibility, and thunderstorms/Cumulonimbus into a meteogram dashboard. See here our components, recipes, and results:



Wind machine learning

Predicting airport capacity by wind regime

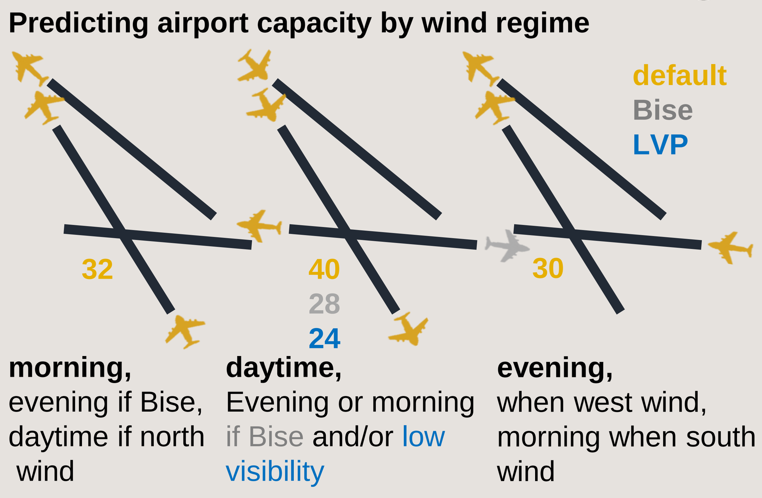


Figure 1: Capacity (airplane movements per hour) at Zurich Airport at different times and during particular weather conditions (simplified)

ML method:

- Temporal Fusion Transformer Model (probabilistic time series prediction)
- Predictors:
  1. wind measurements (which are also target variables) from different stations at and around the airport
  2. NWP predictions from COSMO-1E (CTRL run)
- Targets: u- and v-component of the 2 min average and gust winds
- Temporal resolution: 10 min till T+2h
- Spatial resolution: currently one station at North of airport Zurich

Results: Example 30 min prediction

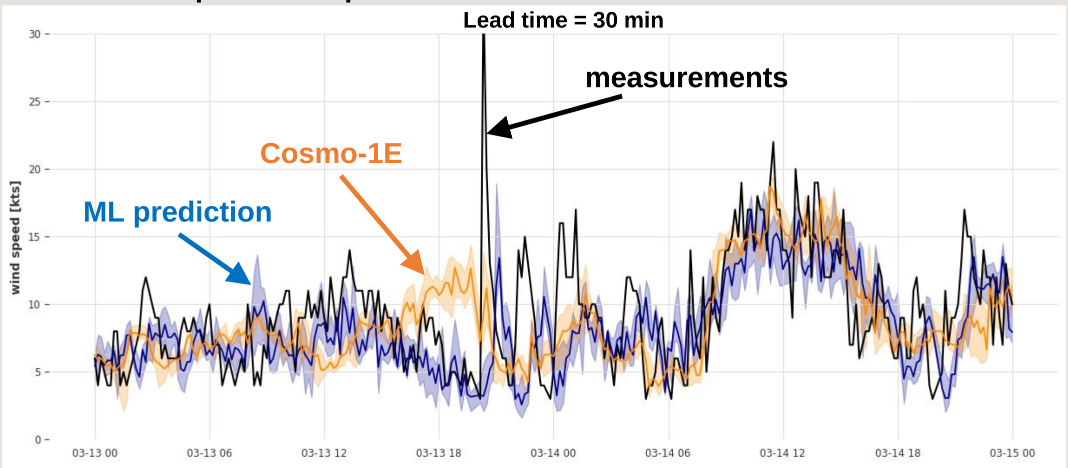


Figure 2: Example wind speed prediction with a 30 min lead time (from «now») between 13.03.2023 - 15.03.2023 at airport Zurich. Measurements are shown in black, Cosmo-1E 10 min ensemble predictions are in orange and the ML prediction is in blue (median + minimum to maximum ensemble range).

Visibility machine learning

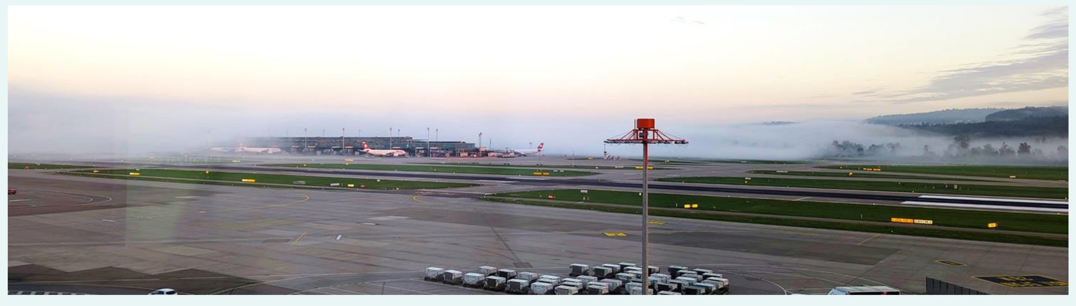


Figure 3: Low visibility conditions at Zurich airport. Photo: H. Barras

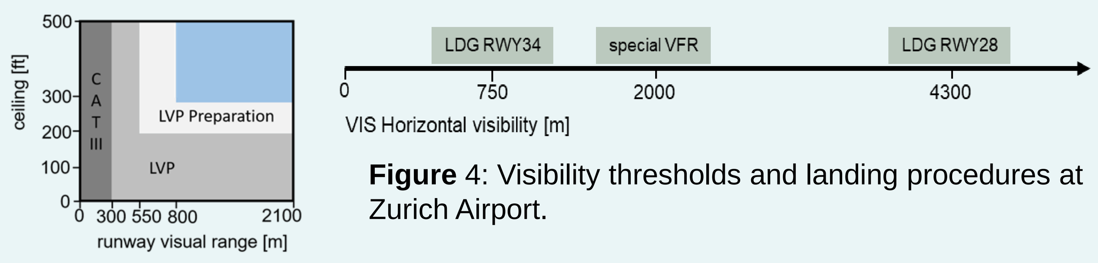


Figure 4: Visibility thresholds and landing procedures at Zurich Airport.

ML method:

- Temporal Fusion Transformer Model (probabilistic time series prediction)
- Predictors:
  1. observed horizontal and vertical visibility from different stations at and around the airport
  2. observed solar radiation, humidity, temperature, wind, precipitation and pressure at the airport
  3. NWP predictions from COSMO-1E (CTRL run)
- Targets: horizontal and vertical visibility (ceiling)
- Temporal resolution: 10 min till T+2h
- Spatial resolution: currently one station at the North of airport Zurich

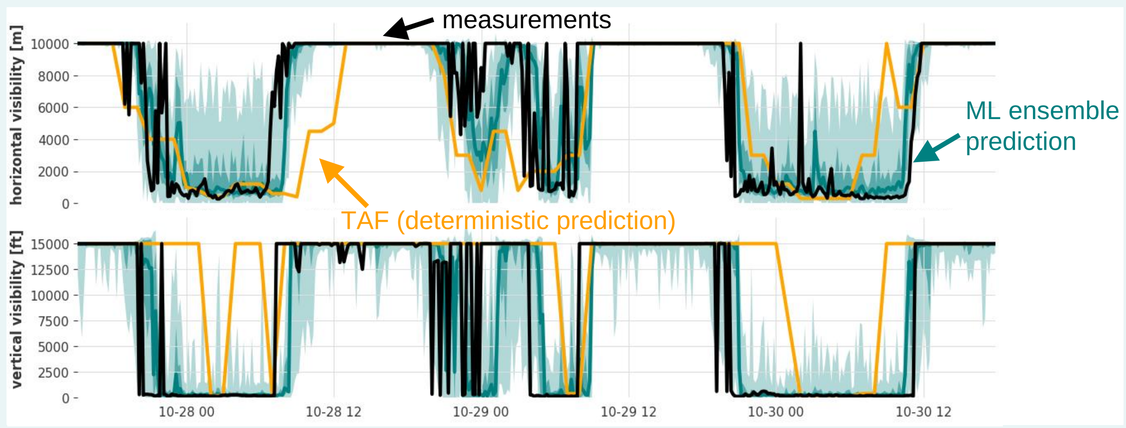


Figure 5: Example prediction for horizontal visibility (top) and vertical visibility (bottom) between 27.10.2022 15UTC and 30.10.2022 18UTC with a lead time of 60 min in the North of Zurich Airport. Measurements are shown in black, prediction from the operational deterministic product, TAF, in orange and the ML ensemble predictions in turquoise. The turquoise shadings indicate the 5%-95% range (light shading) and the 25%-75% range (dark shading).

Thunderstorm machine learning

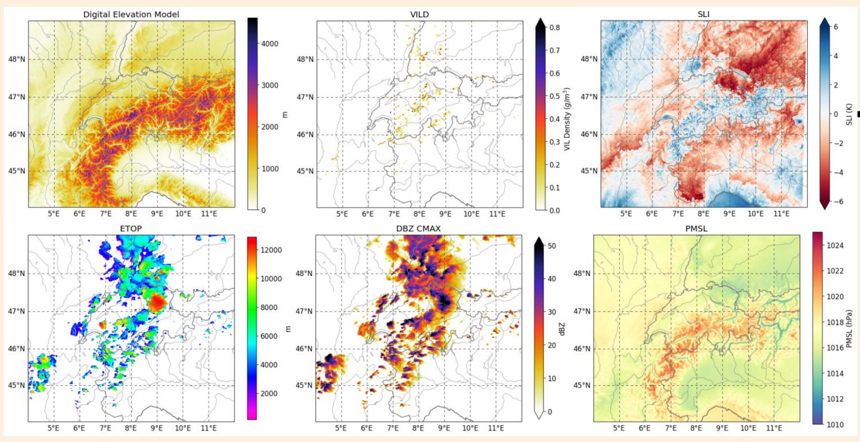
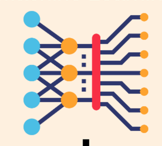


Figure 6: Selection of NWP fields used as features for machine learning.

Machine Learning



Goal

- Provide probabilistic convection forecast to support air navigation service provider
- Based on NWP forecasts from COSMO-1E / ICON-CH1-EPS
- Use machine learning to reduce false positives

ML method:

- Random Forest (XGBoost, LightGBM) trained using different NWP fields as features and up-scaled lightning observations as target (>1 flash / 30min / 8km)
- Temporal resolution: Hourly predictions from T+2 until T+12h

Direct model output

- Based on explicit NWP convection prediction
- NWP model overconfident
- Requires calibration to reduce overprediction
- Easily interpretable
- Can be quickly implemented using few thresholds (e.g. upscaled probability of > 40 dBZ)

ML prediction

- Based on a selection of NWP parameters
- Reduced false positives but also more misses
- ML model produces calibrated forecasts
- Black-box predictions
- Requires a lot of data for training (ideally more than 1 season)

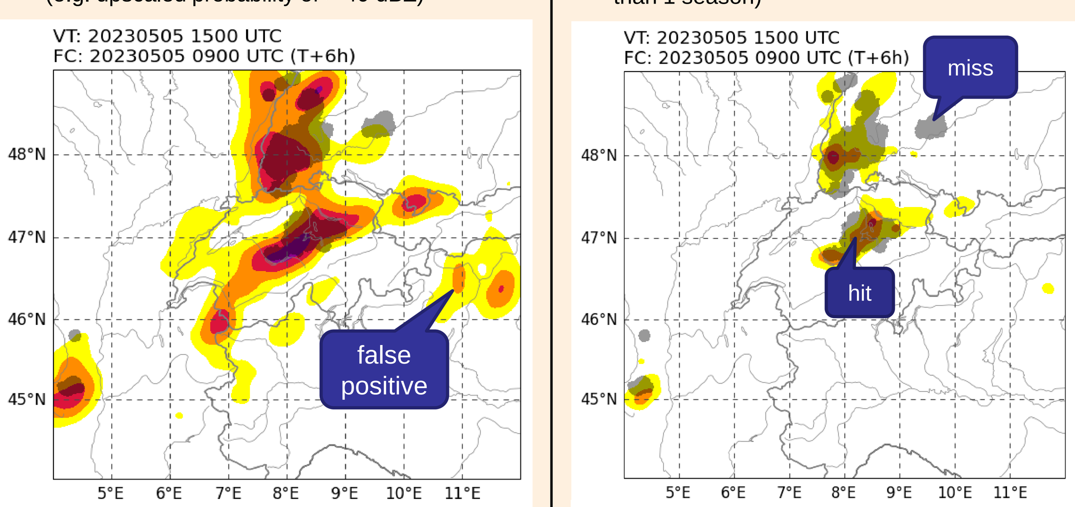


Figure 7: Convection forecast at T+6h using NWP (left) and ML approach (right). The grey shading highlights regions with observed lightning.

Probabilistic meteogram (excerpt):

Methods: Python (dash/plotly) meteogram, versioned in GitLab, CI/CD Jenkins, containerized in OpenShift (kubernetes).
Contents: wind, temperature, QNH, horizontal/vertical visibility, CB/TS, precipitation
Goals: Convey more information to our users, enable a better decision-making for aircraft operations

„Correct numbers" vs. full decision base

One of our main customer requirements is to obtain „correct numbers" from us.
For you as an expert in the field, would you feel more comfortable with having the entire uncertainty information on weather prediction for making air traffic decisions?
Or would you prefer having „hard numbers" which can also be sometimes „wrong" and cause you more trouble when airplanes need to go into holding or have to perform go arounds?
Share your opinion with us in the box below or talk to Johannes!

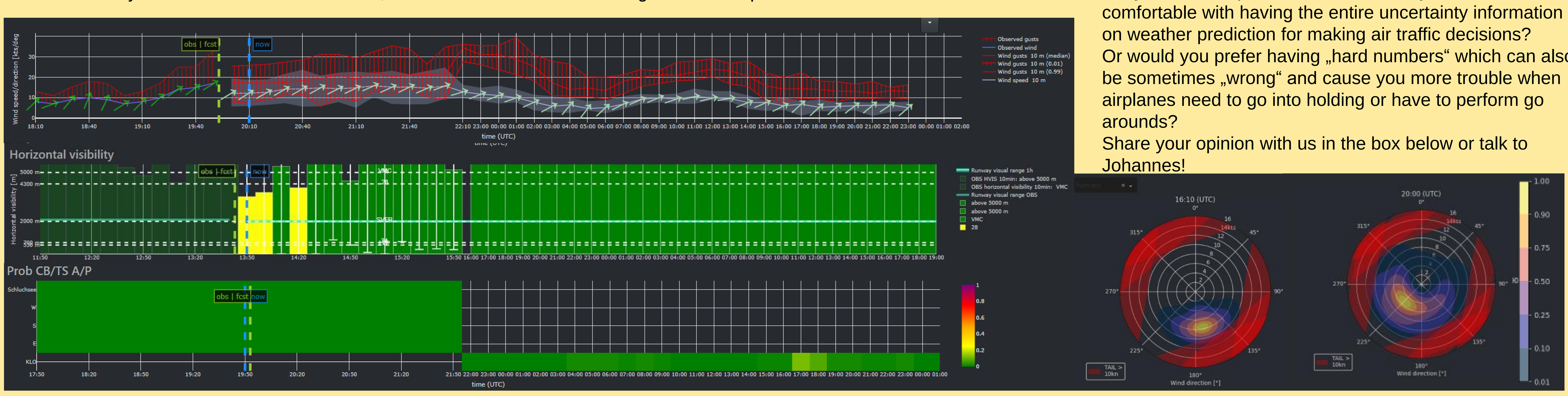


Figure 8: The metogram with probabilistic information gathered from the machine learning, supplemented with COSMO-1E and TAF Guidance data. From top to bottom and left to right, here are example forecasts for: (1) wind, presented as a line plot with shaded/hatched percentiles around the median wind and gusts, (2), horizontal visibility and runway visual range, presented as a bar charts with error bars; bar colors are changed with respect to air traffic relevant thresholds (white dashed lines), (3) probability of thunderstorms/CB in the TMA areas of Zurich airport and at the airport itself (longer lead times), and (4) two probabilistic wind roses with tail wind thresholds (10kts) highlighted for the runways of the airport

Your ideas/comments/opinions:

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