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Low-Visibility Forecasts: Direct Model Output vs. Statistical Postprocessing

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In a Nutshell

Probabilistic forecasts for low-visibility conditions, relevant for flight planning, are developed from direct output of the ECMWF model forecasts and a statistical postprocessing model. The forecasts are compared amongst others and to climatology to indicate the most accurate prediction system for different lead times.

Introduction

Safety operations with low visibility:

Instrument landing approach
Increased **spacing distances**
and **taxiing times**

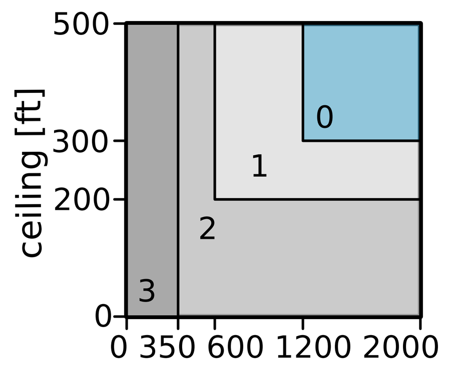
} Decreased **capacity**
Flight **delays**
Economic **loss**

Accurate forecasts of low visibility allow: Forecast range:
Flight plan **regulations** ⟶ nowcast
Better long-term **flight planning** ⟶ medium-range

Low-Visibility Procedure (*lvp*) States

- Define **safety procedures** during low visibility that **reduce airport capacity**
- Occur mainly with **fog**, **low ceiling**, or **heavy precipitation**

Categories of *lvp* at **Vienna Airport**:



lvp	capacity	occurrence
0	100%	89.7%
1	70%	1.7%
2	60%	7.1%
3	40%	1.5%

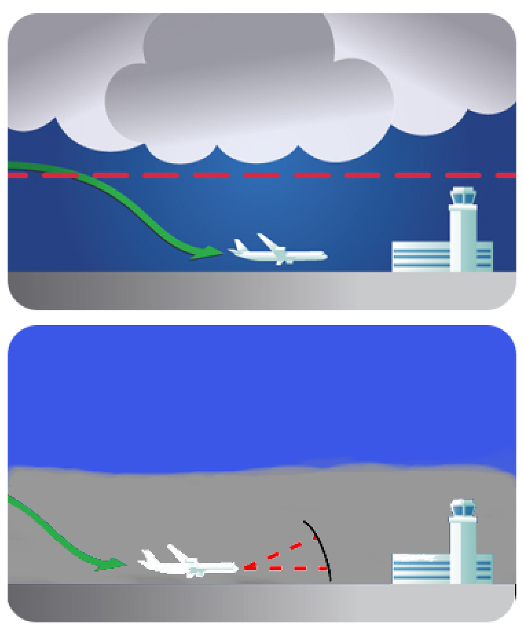


Figure 1: Illustration of **ceiling** (top) and **runway visual range** (bottom).

Postprocessing Method

Train a **statistical model** with **outputs** from **ECMWF NWP models**

- **Statistical model** used for postprocessing: **Boosting Tree**

Model Development:

1. Develop a single **decision tree**
2. Compute **residuals*** of the model
3. Fit a **new tree** on the residuals
4. **Add** new tree to previous ones
5. **Repeat** recursively steps 2–4

* negative gradient vector of the likelihood function

Figure 2: Schematic illustration of the model.

- **NWP output used** for the statistical models:

Variable	Unit	Description	Variable	Unit	Description
bld	[Jm^{-2}]	boundary layer dissipation	***dts***	[°C]	temp. difference to surface
blh	[m]	boundary layer height	***lcc***	[0 – 1]	low cloud cover
e	[m.w.e]	evaporation	***shf***	[Jm^{-2}]	sensible heat flux
cdir	[Jm^{-2}]	clear sky direct solar radiation	***tp***	[m]	total precipitation
dpd	[°C]	dew point depression			

The NWP models used are the ECMWF deterministic high resolution model (**HRES**) and the ensemble prediction system (**ENS**). From the ENS only mean and spread are used. The predictors are selected with the results of Herman and Schumacher (2016) and meteorological expertise. The maximum lead time of HRES is 10 days; for the ENS it is 15 days.

- Models are developed with data from **5 cold seasons** (2011–2017)

References:
Herman G. R. and Schumacher R. S., 2016: Using Reforecasts to Improve Forecasting of Fog and Visibility for Aviation. Weather and Forecasting, **31**, 467-482, https://doi.org/10.1175/WAF-D-15-0108.1.

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Postprocessed Probabilistic Model Forecasts

- **Forecast performance**

	> 11 days	≥ 7 days	≥ 3 days	≥ 1 day	< 1 day
climatology	∼	∼	∼	∼	∼
m(HRES)		∼	+	+++	+++++
m(ENS)	∼	+	++	+++	++++

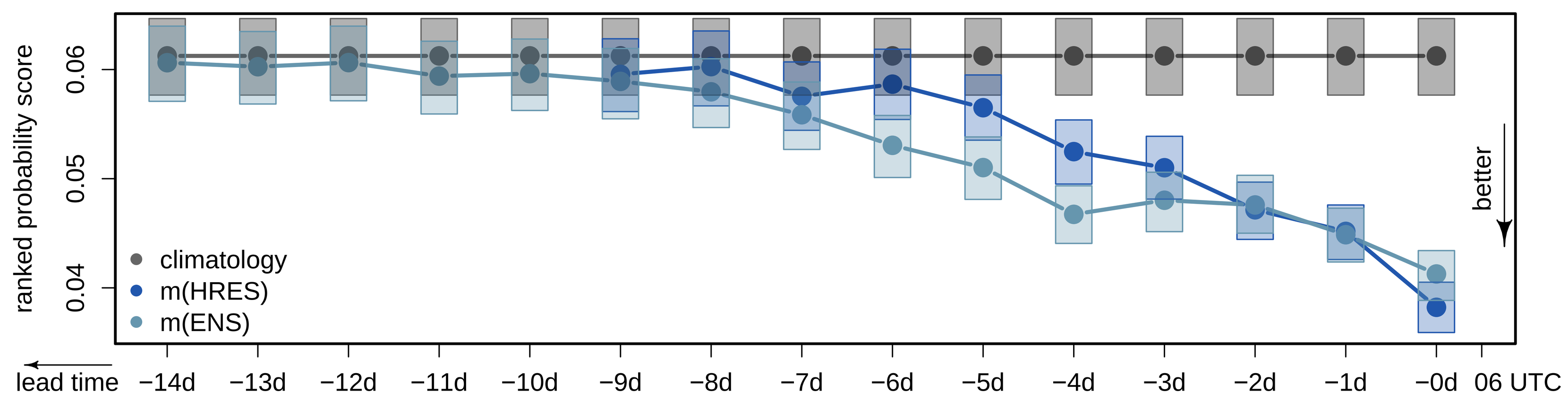

Figure 3: Forecast performance of **climatology** the and statistical models based on outputs of the **HRES** and **ENS** due to the *lvp* state. **Nowcasts** are defined with lead times shorter than 1 day, **medium-range forecasts** with lead times from 1 day up to 11 days. After 11 days the **forecast**s converge strongly to climatology and their **predictability limit** is reached.

- **Variables with highest impact**

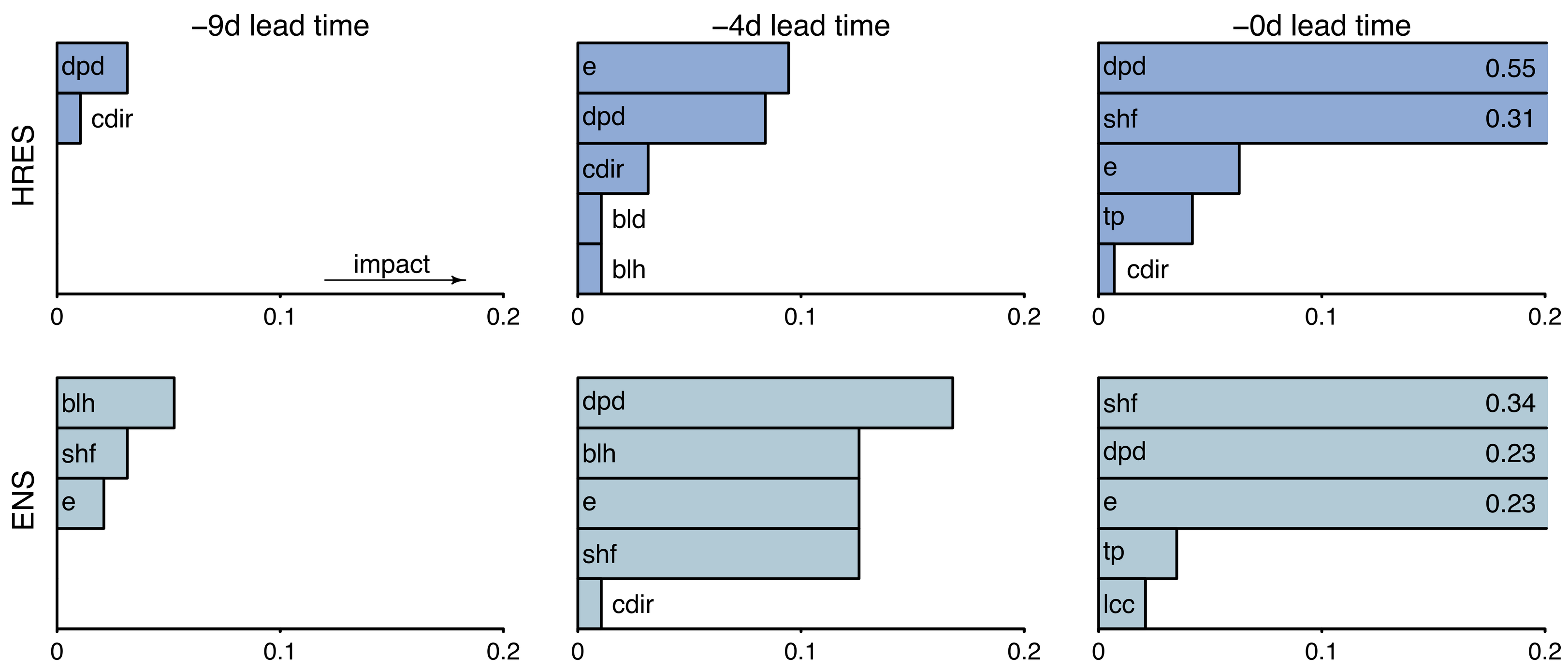

Figure 4: Variables with **highest impact** for postprocessed forecasts based on **HRES** and **ENS** models. The impact of **individual predictors** on the forecast decreases with longer lead times. This analysis is computed with the **variable permutation test**.

Direct Output vs. Postprocessed Output (since 12/2016)

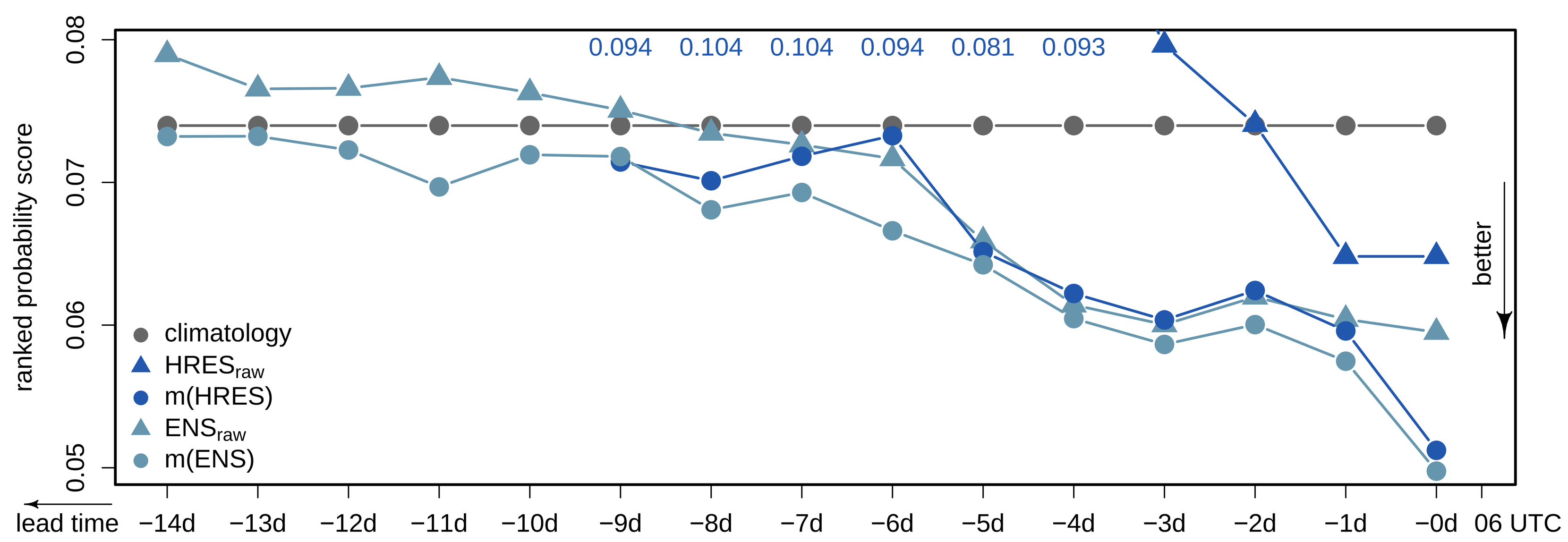

Figure 5: Performance of forecasts based on **climatology**, **raw outputs** from the HRES and ENS, and **postprocessed outputs** from the HRES and ENS. Forecasts of *lvp* from raw outputs are computed by the NWP outputs **visibility** and **ceiling** (available since 12/2016). The validation period is 1.5 cold seasons, the training period of the models and climatology 3.5 cold seasons.

- Postprocessed forecasts **perform best** at each lead time
- Raw ENS always **outperforms** raw HRES
- **Benefit** of raw ENS over climatology until 7 days lead time
- **Skill** between postprocessed forecasts and raw ENS is smallest between 1 and 5 days lead time

Take Home Message

- **Statistical based forecasts** of the *lvp* state...
  ... perform better than **raw NWP model outputs**
  ... have a benefit over **climatology** until 12 days lead time
- Most important predictor variables are dew point depression, boundary layer height, evaporation, and sensible heat flux