Heidelberg Institute for Theoretical Studies HITS

Trends in the predictive performance of raw ensemble weather forecasts

ECMWF

1. Introduction

The European Centre for Medium-Range Weather Forecasts (ECMWF) issues global forecasts consisting of a 50 member ensemble, a high-resolution, and a control run. Such ensemble forecast systems tend to be biased and underdispersive for surface weather variables (Bougeault et al., 2010; Park et al. 2010). Bias and underdispersion can be reduced by different statistical post-processing methods, of which ensemble model output statistics (EMOS, Gneiting et al. 2005) is applied here. EMOS converts an ensemble of K discrete forecasts $\boldsymbol{f} = (f_1, f_2, \ldots, f_K)^T$ into a predictive density:

$$y|\boldsymbol{f} \sim g(m, \sigma), \tag{1}$$

where $g(\cdot)$ is a parametric density function with location and scale parameters m and σ, respectively, which depend on the raw ensemble. Typically, post-processing increases forecast skill. Skill of probabilistic forecasts is often measured by the negatively oriented continuous ranked probability score (CRPS, Hersbach 2000):

$$\text{CRPS}(F, y) = \int_{-\infty}^{\infty} \left[F(x) - \mathbb{1}_{[x \geq y]}\right]^2 dx, \tag{2}$$

where F is the predictive CDF and y is the verifying observation. Figure 1 shows CRPS values of the raw ensemble and the EMOS forecasts for the variables 2 m temperature (T2M), 24 h precipitation (PPT24), and near surface wind speed (V10).

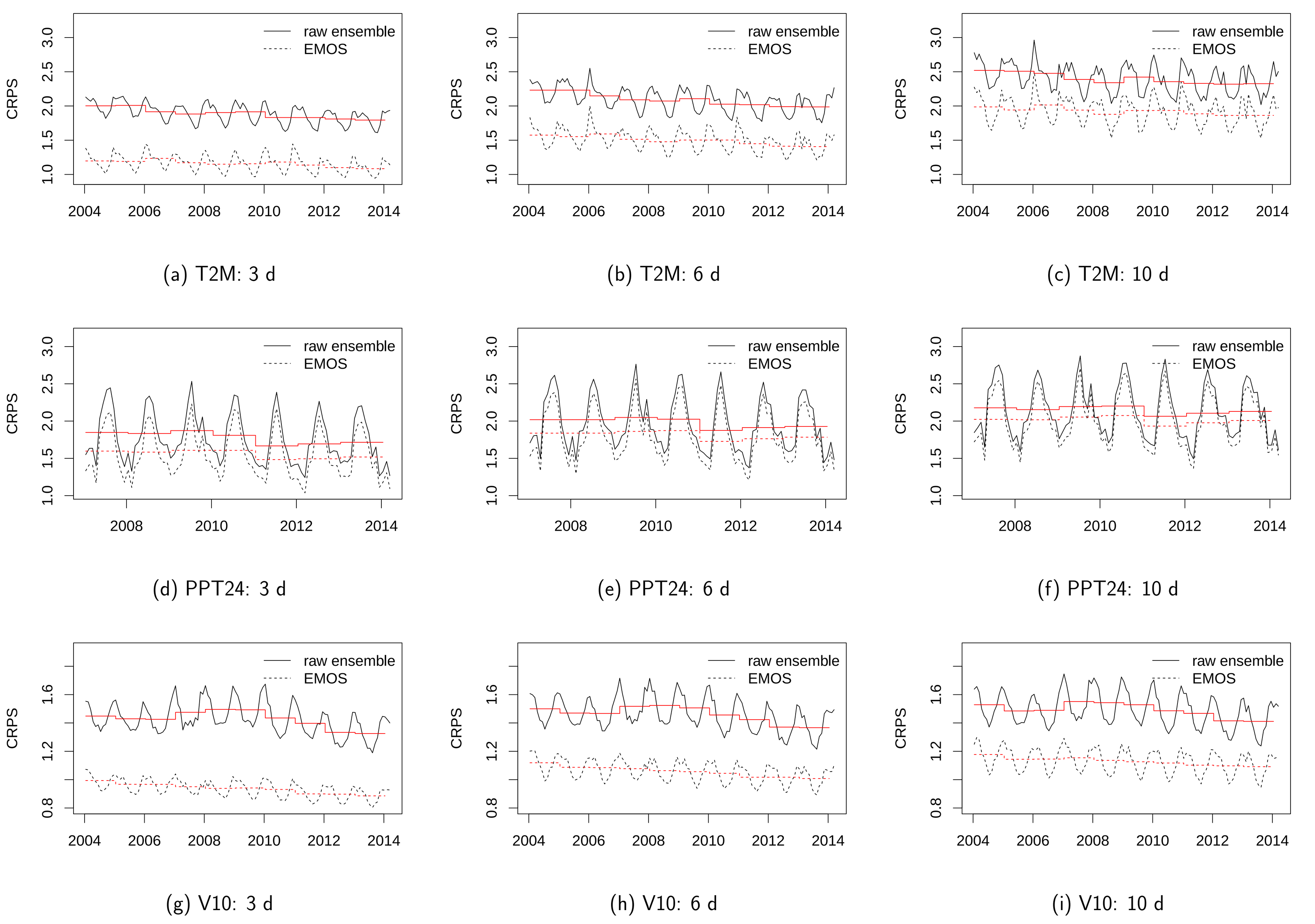

Fig.1: Global averages of CRPS for forecast lead times of 3, 6, and 10 days.

2. Research question and methods

The ECMWF forecast ensemble is under continuous development (Buizza et al., 1998, 2007; Richardson et al., 2013; Haiden et al., 2014). Hence, its forecast skill improves over time due to the following causes:

1. bias reductions and increased reliability → competes with statistical post-processing
2. an increase in potential skill → complementary to statistical post-processing.

In order to determine which of the above causes is more important, the evolution of the CRPS difference $\Delta\text{CRPS}_t = \text{CRPS}_{\text{raw},t} - \text{CRPS}_{\text{EMOS},t}$ is evaluated over time (Hemri et al, 2014). The following two approaches are used:

- Fit a parametric regression model to ΔCRPS_t and evaluate the estimates $\hat{\beta}_1$:

$$\Delta\text{CRPS}_t = \beta_0 + \beta_1 t + \beta_2 \sin\left(\frac{2\pi t}{12}\right) + \beta_3 \cos\left(\frac{2\pi t}{12}\right) + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2) \tag{3}$$

- Correct for seasonal effects by fitting the following model to ΔCRPS_t:

$$\Delta\text{CRPS}_t = \gamma_0 + \gamma_1 \sin\left(\frac{2\pi t}{12}\right) + \gamma_2 \cos\left(\frac{2\pi t}{12}\right) + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2), \tag{4}$$

and then use the non-parametric Kendall's τ rank correlation test to check for a significant trend in the residuals of model (4).

These models are fitted for each variable, station, and lead time seperately. Two examples for ECMWF forecasts with a lead time of 6 days are shown in figure 2.

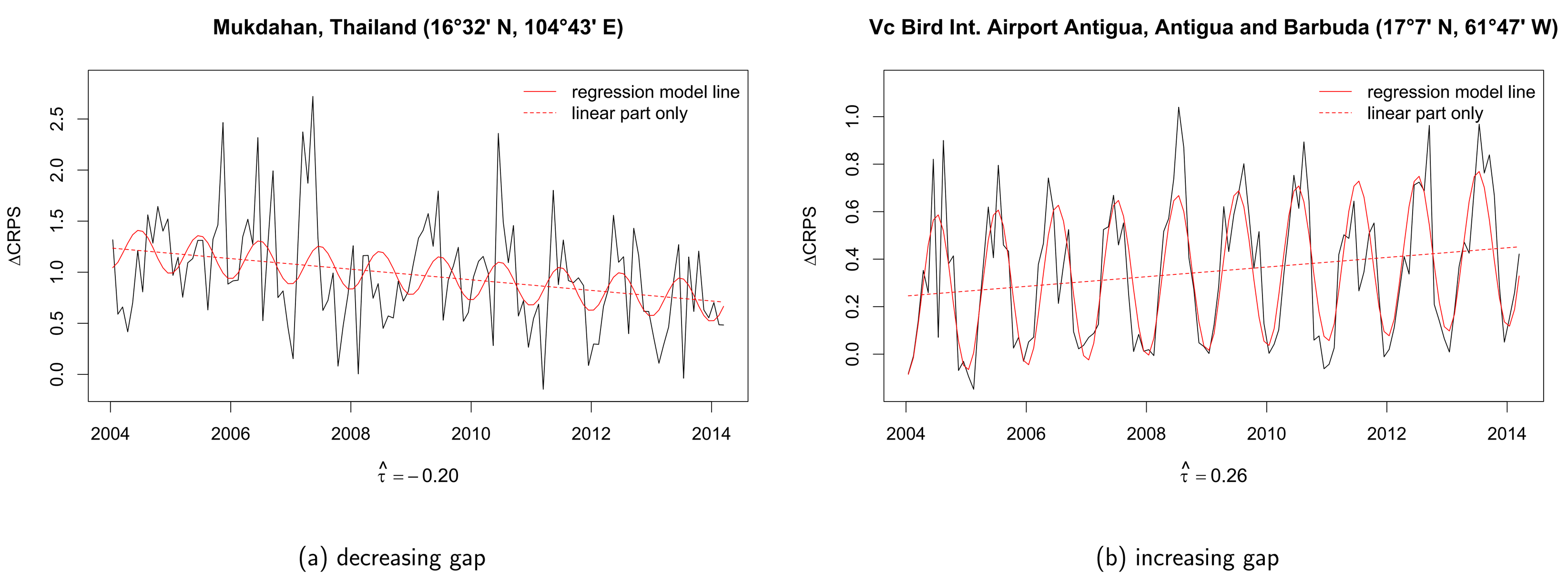

Fig.2: Trends in ΔCRPS for T2M at two example stations.

3. Results

There is no clear trend in ΔCRPS. Table 1 shows the percentages of SYNOP stations (totals are 4160 (T2M), 2917 (PPT24), and 4387 (V10)) showing no, negative, or positive trend in monthly ΔCRPS values against time at a significance level of 0.05. Stations with no significant trend outnumber the stations with either negative or positive trend.

Tab.1: Percentages of stations with significant trend in ΔCRPS.

forecast lead time		parametric model			Kendall's τ statistics		
		T2M	PPT24	V10	T2M	PPT24	V10
3 d	no significant trend	42 %	76 %	41 %	44 %	77 %	42 %
	negative trend	34 %	19 %	31 %	32 %	18 %	29 %
	positive trend	24 %	5 %	28 %	24 %	5 %	29 %
6 d	no significant trend	46 %	82 %	43 %	48 %	82 %	45 %
	negative trend	31 %	14 %	31 %	29 %	13 %	29 %
	positive trend	23 %	4 %	26 %	23 %	5 %	27 %
10 d	no significant trend	54 %	83 %	45 %	54 %	82 %	46 %
	negative trend	27 %	11 %	31 %	26 %	11 %	28 %
	positive trend	19 %	6 %	25 %	20 %	7 %	26 %

A station-wise assessment of significant trend in ΔCRPS is shown in figure 3:

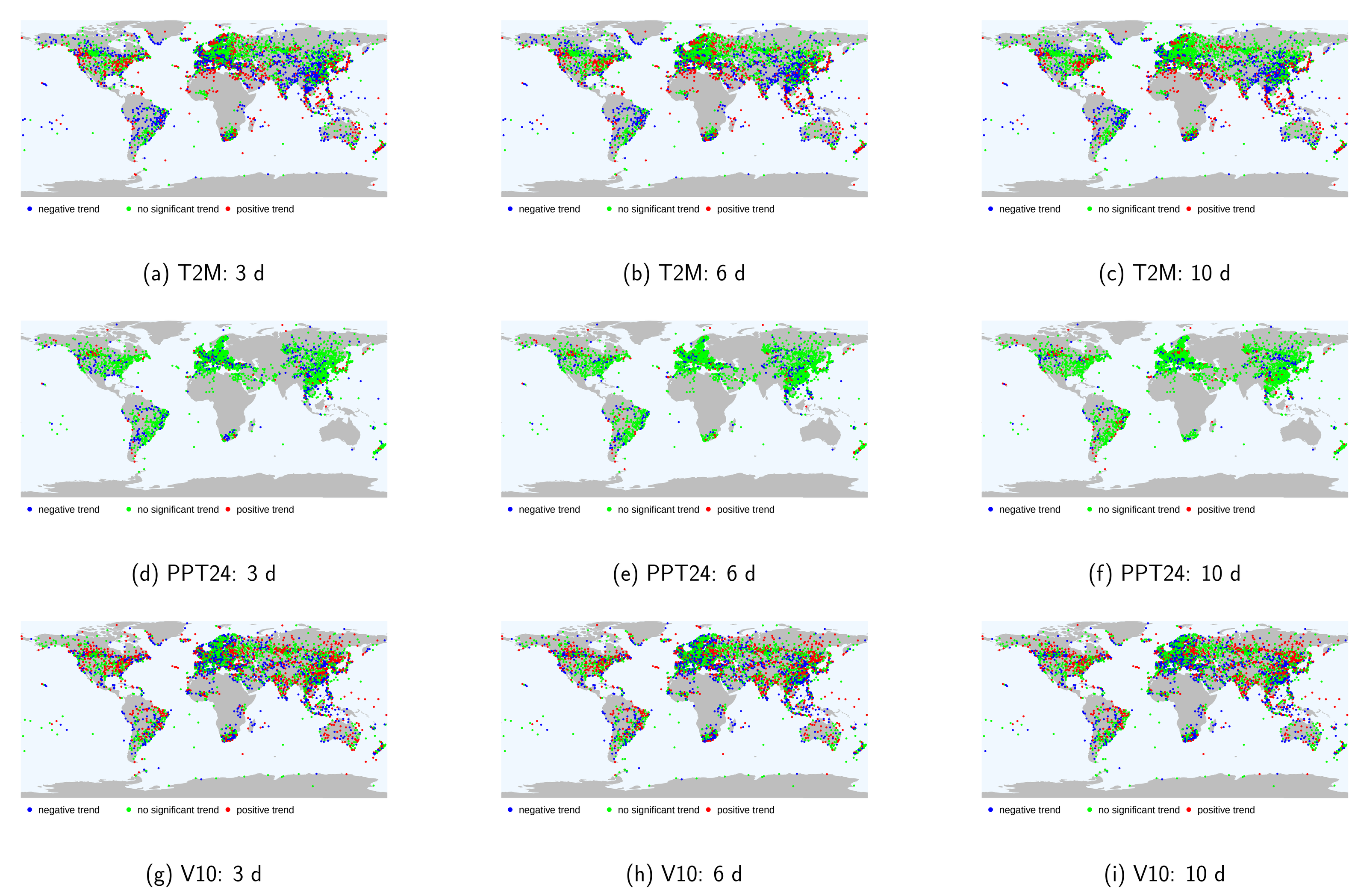

Fig.3: Significants trend in ΔCRPS according to the Kendall's τ correlation coefficient test.

4. Conclusions

- Skill of both the raw ensemble and the EMOS forecasts improves over time.
- The gap in ΔCRPS remains almost constant over time.
- Improvements to the atmospheric model are increasing potential skill.
- Statistical post-processing will keep adding skill in the foreseeable future.

5. References

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