NOWCASTING OF PRECIPITATION

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1. INTRODUCTION

Short-term methods of precipitation nowcasting range from the simple use of regional numerical forecasts to complex radar data assimilation schemes. Presently, the skill of numerical models is rather poor for precipitation. Figure 1 shows some typical scores for precipitation detection for two limited area models. The skill is low, thus, nowcasting presently requires other, mostly heuristic, techniques.

We will give here a brief description of the method most commonly used operationally, that is, the method based on persistence of the precipitation pattern in the moving coordinates (Lagrangian Persistence, or LP for short).

All the skill values and diagrams presented here were obtained for the Central-Eastern United States (that is excluding the mountainous regions) and are certainly not universal results

2. NOWCASTING BY LP

In this method the immediate past of the precipitation patterns is used to determine the field of motion of the pattern. Then this field of motion is used to forward advect the present pattern. Longer lead times of the nowcast are given by further advection. The quality of this method depends on many factors but an important one is the availability of radar composites. Single radar LP nowcast have useful skill for up to one hour only. The limiting factor is the impossibility of seeing far enough to predict what will be arriving. In addition, the field of motion is poorly evaluated due to range effects of scanning radar. With continental scale composites the useful lead times extend up to six hours.

Obviously, the physical limit to the predictability by LP is growth and decay (including generation of new regions of
precipitation). Let us point out that LP includes some growth and decay. For example, if there is some persistent dissipation at the rear of a system this will result in a motion pattern that is confluent. If the dissipation at the rear continues into the future the advection will capture the narrowing of the pattern.

The example above illustrates that the method of determining the velocity field and pattern advection are critical to the method’s skill.

Another physical limitation of LP is the evolution of the motion field. Figure 3 shows that around 20% of loss of skill (defined here as the time to decorrelation to 1/e) is due to time evolution of motion field.

Predictability of meteorological fields is scale dependent and the fundamental limit to predictability due to non-linearity of the processes governing precipitation is a difficult issue beyond the scope of this discussion.

Here, the term predictability is used denote the limit of skill of the method of forecast used. In relation to LP we note that small cells evolve rapidly and therefore are less predictable that large scale systems. Haar wavelet scale decomposition was used to compare nowcasts of radar precipitation patterns and radar observed patterns at the nowcast time for
different scales. An analysis of four days of data is summarized in Figure 4.

![Wavelet Low-Pass Lifetime](image)

**Figure 4.** Life-time (as defined by the time to decorrelation to $1/e$) for four days of data as a function of filtered out scales.

Since the loss of predictability is faster the smaller the scale of the precipitation pattern, a scale filtering, increasing with lead-time, is needed to avoid attempts at predicting the unpredictable.

An evaluation of the skill in precipitation detection of a particular algorithm of LP nowcast (MAPLE, McGill Algorithm for Precipitation nowcasting by Lagrangian Extrapolation), the filtered nowcast (O-MAPLE, Optimized MAPLE) as well as numerical model outputs is shown in Fig. 5.

![Skill scores of nowcasting by LP (unfiltered and filtered) compared to numerical model outputs.](image)

**Figure 5.** Skill scores of nowcasting by LP (unfiltered and filtered) compared to numerical model outputs.

In relation to this there is another issue that requires a statistical approach. Nowcasting of precipitation intensity based on radar data relies on the transformation from reflectivity $Z$ to rain rate $R$. The $Z$-$R$ relationship has a strong stochastic component that is related to the physical processes responsible for the formation of different raindrop size distributions. These processes are not totally random (in the Gaussian sense). On the contrary, they are quite structured and correlated in space and time. Thus the differences in the fields of $Z$ and

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R are also structured with spatial and temporal scales of correlation.

Figure 6. A rain rate field obtained from Z to R transformation by a climatological Z-R relationship and four stochastic realizations of the R-filed that have the same mean, variance and correlation structure of the variability in the Z-R relationship around the climatological one.

Figure 6 shows four plausible fields of rain rate that correspond to a single reflectivity filed. These four fields are members of an ensemble that incorporates the uncertainty in the Z-R relationship. To produce these realizations we analyze the fluctuations around a mean Z-R relationship as given by disdrometric observations. In particular we determine the correlation between Z and R, the variance of the fluctuations around a mean regression and the time structure function of these fluctuations. A self-affine cascade is then generated that respects the observed stochastic properties and the result is added to the deterministic R-field obtained by the transformation from Z to R using the mean Z-R regression. Each realization of the self-affine cascade produces a member of the ensemble. The average of the ensemble is the deterministic R-field. The procedure is similar to the one used by Bowler et al. (2004) to downscale model outputs in order to generate ensemble nowcasts.

In the same manner one can generate an ensemble that contains as well other errors in radar measurements (notably extrapolation...
to ground) and the uncertainty due to the non-predictability of the small scales.

3. COMBINING MODEL AND NOWCASTS

Figure 7 shows the critical success index of the weighted (by the skill of each member in the immediate past) average of precipitation patterns of ensembles made of LP nowcasts and numerical model outputs.

![Figure 7. Skill scores of precipitation forecasted by a numerical model, of filtered and non-filtered LP nowcasting and their weighted combinations.](image)

Although the WRF model performance is rather poor when combined with LP nowcasts it leads to significant improvement in skill. For short lead times, up to three hours, MAPLE is superior. The addition of the filtered nowcast, O-MAPLE, helps to improve the score. All this is case dependent. Fig. 8 shows the detection CSI for cases where model performance was particularly good (WRF model CSI at least 1.4 times the one in Fig. 7). These cases represent 8.8% of the analyzed period.

![Figure 8. Same as Fig. 7 but for cases where WRF skill was significantly above the average](image)

Again MAPLE outperforms model for lead times of up to 3 hours. However, in this limited sample scale filtering was particularly effective at increasing the score. On the other hand, the score of the ensemble including the filtered LP nowcast is not as good as without it. All this points out to the need of carefully adapting the algorithm to each situation.

4. FINAL COMMENTS

Nowcasting by LP, introduced over three decades ago, remains still the choice method for operational nowcasting. It has better skill than present days numerical models for up to six hours. However, this statement must be made with caution since radar maps are used for verification and consequently privileged radar based nowcasts. It should be also pointed out that LP nowcasts are only good in regions where advection of precipitation dominates over generation. In mountainous
regions LP has little skill (this also holds for NWP).

Further improvements in the skill of LP nowcasts will be difficult to achieve. Attempts at incorporating tendencies have been unsuccessful. The motion field already captures growth and decay that leads to persistent changes in the pattern.

It is likely that incorporating uncertainties as well as physical information from other sources (including information from NWP) into a stochastic generation of ensembles is the road to follow.

Combination of LP nowcasts with NWP leads to improvement in skill. It is likely that progress in technology, particularly computing capability, will lead to improvements in resolution of numerical models and better data assimilation. We should expect some improvement in NWP. This will be automatically incorporated into the nowcasts obtained by combination of LP nowcasting and NWP.

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REFERENCES


