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Predictability of precipitation from continental radar images – a scale- and location-dependent benchmark to evaluate model forecasts

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Abstract. Predictability of precipitation is examined from the storm to synoptic scales through an experimental approach using continental radar composite images. The lifetime of radar reflectivity patterns in Eulerian and Lagrangian coordinates is taken as a measure of predictability. The results are stratified according to scale, location and time in order to determine how predictability depends on these parameters.

In a Lagrangian persistence framework the predictability problem can be separated into a component associated with growth of precipitation and a component associated with changes in the motion field. The role of changes in the motion field turned out to be small but not negligible. A stratification of lifetime according to the location reveals the regions with high predictability and significant non-stationary motion.

This work is of high practical significance for three reasons: First, Lagrangian persistence of radar patterns was proven to have skill for probabilistic precipitation nowcasting. The discussion of the sources of uncertainty provides a guideline for further improvements. Second, a scale- and location-dependent benchmark is obtained against which the progress of other precipitation forecasting techniques can be evaluated. And, third, the experimental approach to predictability presented here is a valuable contribution to the fundamental question of predictability of precipitation.

1 Outline

Three companion papers printed in peer-reviewed journals give a detailed description of the methodology, and present results obtained for 143 h of North American warm season rainfall with emphasis on lifetime, scale-dependence, optimum smoothing of forecast fields, and predictability in terms of probabilistic rainfall rates (Germann and Zawadzki, 2002, 2004a; Turner et al., 2004). A fourth paper presently in preparation discusses the sources of forecast uncertainty and extends the analysis to a total of 1424 h of rainfall (Germann and Zawadzki, 2004b). Here, we give an introduction to the experimental approach to predictability explored in the above mentioned publications. For details the reader is referred to the literature.

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2 Approaches to predictability

From a purely dynamic point of view predictability is related to the sensitive dependence of the trajectory of the atmospheric state in phase space to small perturbations in the initial conditions. No matter how small the difference between two initial states is, it will grow and eventually be so large that the two atmospheric states are no more similar than any randomly chosen pair of possible states. This sensitivity is an intrinsic and fundamental property of any nonlinear system, and is referred to as the initial value problem. For a simple low-dimensional system it can be investigated analytically. But, as soon as the system becomes complicated, as is the case for the atmosphere, it is difficult to study its predictability. Then, any approach can only give an estimate of the true predictability.

There is a variety of studies that allow inferences of the predictability of the atmosphere: some follow a purely analytical approach, others are more of experimental character. Table 1 gives an overview of predictability studies including some selected references.

An example of a purely analytical approach is the evaluation of the Liouville equation to examine perturbation growth of a dynamic system. The Liouville equation, introduced in a meteorological context by Gleeson (1966) and Epstein (1969), describes the evolution of probability density of the atmospheric state in phase space, and is the analog to the equation of mass conservation in physical space. It states that realizations of the state of a system can not spontaneously appear or disappear. Principally, it can be solved analytically

Table 1. Experimental and analytical approaches to predictability.

purely experimental approach
Studies with observations autocorrelation and spectral analysis (Lorenz, 1973; Zawadzki, 1973) analogs and periodicity (Lorenz, 1993), interdependence (Zawadzki et al., 1981; Lilly, 1986) precursor and predictor analysis Hovmöller diagram (Carbone et al., 2002), composite analysis
Studies with statistical models forecast skill as evaluated against observations: Lagrangian persistence (Zawadzki et al., 1994; Germann and Zawadzki, 2002) dependence on scale (Lorenz, 1969; Germann and Zawadzki, 2002; Turner et al., 2004) dependence on location (Germann and Zawadzki, 2004b) and weather
Studies with numerical weather prediction models forecast skill as evaluated against observations sensitivity to initial conditions: singular vectors (Ehrendorfer et al., 1999), ensembles (Palmer, 2002; Buizza et al., 1999) precursor analysis (Massacand et al., 1998)
Studies with idealized systems of dynamic equations Liouville equation (Gleeson, 1966; Epstein, 1969; Ehrendorfer, 1994,b) Lyapunov exponent Lorenz model, attractor (Lorenz, 1963; Palmer, 1993)
purely analytical approach

for any dynamic system, but in practice it is only applicable to low-dimensional problems, such as a one-dimensional Riccati equation (Ehrendorfer, 1994).

On the other end of the spectrum of predictability studies are those purely based on observations, such as autocorrelation analysis of the variable of interest (Lorenz, 1973; Zawadzki, 1973), or studies looking for precursors in the observation space. Between the purely analytical and purely experimental approach there is a variety of studies employing statistical and numerical weather prediction models, which combine analytical concepts with observations. In a model approach predictability can be measured by the skill of the model to predict a certain phenomenon as evaluated by statistical comparison with observations, or by the growth of initially small perturbations in model phase space using singular vector analysis or ensembles of model runs.

The analytical approach allows to understand basic concepts of nonlinearity, perturbation growth, and sensitive dependence. But, as studies with idealized systems of dynamic equations or with state-of-the-art numerical weather prediction models both assume the model to be representative of the true system, the crux lies in all sorts of model errors. These include errors in the model structure, lack of resolution, errors in scale interactions, inadequate parametrisation, parameter uncertainty, problems in boundary conditions if running a regional model, and numerical and computational errors that result for instance from finite difference schemes. In practice it is difficult to separate the problem of predictability into a component associated with initial error and a component associated with model error (Palmer, 2002). The validity of the results of predictability studies using numerical weather prediction models can be very sensitive to model errors. Another difficulty comes from the dimension and complexity of the weather system which makes analytical approaches computationally expensive or unpracticable.

3 Predictability of precipitation

The fact that precipitation is an indirect product of numerical modelling that relays on a relatively crude parametrisation of convection and microphysics makes the problem even more complicated than illustrated above. In fact only very few results have been presented on the predictability of precipitation. One way to obtain a quantitative scale-dependent estimate of the predictability of precipitation is to examine Eulerian and Lagrangian persistence of radar precipitation patterns, introduced in a series of companion papers (Germann and Zawadzki, 2002, 2004a; Turner et al., 2004).

The basic idea is to take the skill of forecasts obtained from Eulerian and Lagrangian persistence of large-scale radar composite images as a measure of predictability. An Eulerian persistence forecast is obtained by keeping the image frozen

$$\hat{\Psi}(t_0 + \tau, \mathbf{x}) = \Psi(t_0, \mathbf{x}) \quad (1)$$

where Ψ is the observed precipitation field, t_0 is the start time of the forecast, τ is the lead time, and $\hat{\Psi}(t_0+\tau, \mathbf{x})$ is the forecasted rate at time $t_0 + \tau$ and position $\mathbf{x}$. By advecting the precipitation patterns following the field of echo motion we obtain a Lagrangian persistence forecast

$$\hat{\Psi}(t_0 + \tau, \mathbf{x}) = \Psi(t_0, \mathbf{x} - \alpha) \quad (2)$$

where α is the Lagrangian displacement vector. The forecast images are then compared to observations at the given lead times to calculate correlation, lifetime and skill scores such as the probability of detection, the false alarm rate and the equivalent threat score. For more details the reader is referred to Germann and Zawadzki (2002). Since this approach is conceptually simple we thus obtain an easy-to-interpret measure of predictability of precipitation. Calculation of lifetime and scores can be stratified according to scale, location, time, and weather, in order to determine the dependence of predictability on these parameters.

A similar stratification of predictability is not straightforward when using a numerical weather prediction model, because both design and parameters of a model have a significant influence on the performance at different scales, locations etc. Of course there are problems in the experimental approaches as well. First there are measurement errors, and, second, there is some difficulty in linking the results to the nonlinear and chaotic nature of the system.

4 Benchmark concept

The concept of taking the skill of a forecasting technique, such as persistence of radar precipitation patterns, as a measure of predictability goes back to Lorenz (1973) who said: "Regardless of what may be indicated by theory, a conclusive proof that partial predictability exists at a given range would be afforded by any demonstration that at least one forecasting procedure exhibits skill at that range". Fig. 1 illustrates this approach. It conceptually shows the skill of different forecasting techniques as a function of lead time. By picking for each lead time the best technique we obtain an envelope curve, which provides a conservative estimate of predictability. We say "conservative" because this estimate will never be above the exact predictability (see for example "Precipitation forecast based on numerical weather prediction models and radar nowcasts" by Lin, Vasic, Zawadzki and Turner; this conference). This approach has high practical significance: First, it tells what is achievable in the forecast office, and, second, it provides a benchmark against which the progress of any forecasting technique can be evaluated.

The concept of Lagrangian persistence of radar precipitation patterns may have a greater distance from the exact atmospheric system than the calculation of precipitation in a numerical weather prediction model. Yet, we can not say a priori which of the two gives a better estimate of predictability of precipitation. At present, any estimate is welcome.

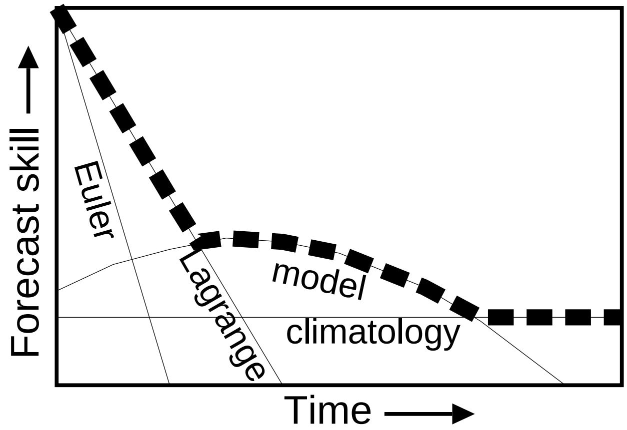

Fig. 1. Benchmark concept.

5 Limits to prediction

The methodology of Lagrangian persistence in the context of predictability studies and nowcasting has been discussed in detail in Germann and Zawadzki (2002, 2004a) and Turner et al. (2004), hereafter referred to as GZ02, GZ04, and TZG04, respectively. GZ02 introduces the techniques and presents first results. GZ04 extends the analysis to probability space, and discusses the question of predictability in terms of probability density of precipitation rates. Fourier and wavelet decomposition is applied in TZG04 to determine how predictability depends on scale, and to define optimum smoothing of forecast fields. A practical outcome is the McGill Algorithm for probabilistic Precipitation nowcasting by Lagrangian Extrapolation including optimum smoothing to reduce rms errors (MAPLE), which is currently being implemented at the Meteorological Service of Canada.

The results presented so far provide a detailed picture of the predictability of precipitation in terms of Eulerian and Lagrangian persistence. A logical next step is to identify the factors that limit predictability, and to quantify their relative importance. This question is central to predictability studies, both from a theoretical and a practical point of view, and has not been addressed yet. It is presently explored in a fourth paper in preparation to be submitted to J. Atmos. Sciences. Generally speaking it is the sources of growth of uncertainty with increasing forecast time that put an upper limit to prediction. In practice it depends on the forecasting technique which are the relevant factors. In a Lagrangian persistence framework there are two orthogonal factors that limit predictability: first, growth and dissipation of precipitation, and, second, changes in the motion field. In other words, there is evolution in the precipitation field and evolution in the motion field that play a role. If both terms were precisely known ahead in time we could combine it with Lagrangian persistence and would thus obtain a perfect forecast. We know from experience that the evolution of precipitation is important. But we do not know its relative importance compared to changes in the motion field, nor do we know how this relation depends on location and time.

Instead of looking for sources of forecast uncertainty, we can also look for sources of certainty, and ask: What are the factors that lead to predictability? First, there is persistence of variables, atmospheric phenomena, and processes that are related to precipitation. Examples are cloud liquid water content, instability, low pressure systems, and uplift of warm air in a warm front, which all exhibit a certain degree of persistence and are somehow linked to precipitation. Second, there is forcing with predictable or partly predictable amplitude, as for instance, the diurnal and annual cycle of net radiation, orographic forcing, Rossby wave dynamics, or latent heat release in a convective updraft. And, third, there are processes and feedback mechanisms that lead to convergence in phase space. The study of Eulerian and Lagrangian persistence of radar precipitation patterns from the storm to synoptic scales is thus an important step towards understanding predictability of precipitation.

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