THE VAISALA RADAR-BASED NOWCASTING SYSTEM

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ABSTRACT

An overview of the Vaisala radar-based nowcasting system is presented. The system, based on the Lagrangian persistence paradigm, is designed to provide targeted quantitative forecasts over the 0–1 h time frame for applications such as aviation, road weather, and renewable energy. The system combines several features previously used separately to enhance performance. The adoption of a modular framework capable of assimilating a variety of data and applying subsets of such features is predicated on the requirement to provide multi-purpose decision support to end-users.

1. INTRODUCTION

The utility of extrapolating radar echoes over the 0–1 h forecast horizon has been shown (Wilson et al. 2010). The Lagrangian persistence paradigm, where extrapolation is performed via motion vectors estimated from past observations held constant over the lead time period, is a useful approach for many nowcasting applications. This method has shown effectiveness in estimating translation of a variety of precipitation patterns.

Previous research has shown that nowcasting performance can be improved by spatially filtering radar observations and considering only those precipitation scales most representative of pattern motion for prediction or filtering those scales from predicted fields deemed unpredictable by remaining past their lifetimes. Additionally, smoothing the estimated motion vector field and extrapolating trends in the data has shown improved performance in some cases. The Vaisala nowcasting system provides the capability to include all or subsets of these features based upon the targeted application.

2. SYSTEM OVERVIEW

The features of the Vaisala nowcasting system are summarized as follows:

1. Resampling to meet runtime requirements
2. Filtering to represent motion of the precipitation pattern envelope (Wolfson et al. 1999; Van Horne et al. 2006)
3. Estimating precipitation pattern motion using cross-correlation template matching (Rinehart 1978; Chornoboy et al. 1994)
4. Smooth motion vector field (Li et al. 1995)
5. Growth and decay trending (Li et al. 1995)
6. Backward-mapping advection (interpolate-once; Germann and Zawadzki 2002)
7. Filtering scales in forecast fields likely contributing to forecast uncertainty (Bellon and Zawadzki 1994)

2. DEMONSTRATION

The features of the system are illustrated for precipitation nowcasting using Vaisala C-band (located at Kerava, Finland), Finnish Meteorological Institute (FMI) Finland national composite, and Unisys U.S. national composite radar data. Fig. 1 shows 0–1 h event-averaged Critical Success Index (CSI; Wilks 2006) scores for the system including each of the features outlined in Section 2 for a single event depicted by each data source. The results show that the inclusion of features improves performance and that different features exhibit the best performance for the different data sets. In particular, motion vector field smoothing using the COTREC method yielded the best performance for the Kerava event and growth and decay trending provided the best performance for the FMI and Unisys events.

Additionally, improvements to the approach developed by Rasmussen et al. (2003) for aviation deicing decision support were observed by first filtering the data used for motion estimation. In this case, Level III radar data collected by the WSR-88D outside of Denver, Colorado, and surface gauge data collected at the Marshall Test Site outside of Boulder, Colorado, were considered.

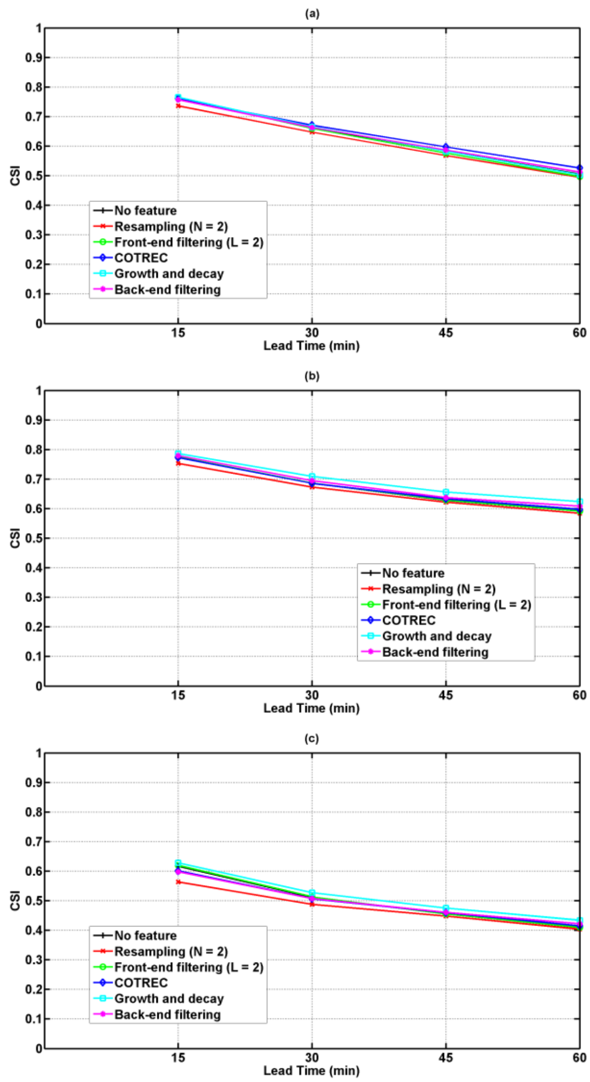

Fig. 1. CSI scores depicting the improvement in nowcasting performance for a single event represented by: a) Vaisala C-band radar at Kerava, Finland, b) FMI Finland national radar composite, and c) Unisys U.S. national radar composite data.

For a winter precipitation event occurring on 12 Dec 2007, the 60-min CSI was observed to increase by about 11% when data used for motion estimation were smoothed by a 10 km × 10 km moving average filter.

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