P1.15 USING AUTOCORRELATION TO EVALUATE PERSISTENCE FORECASTS FOR DISCRETE WIND VECTOR FIELDS IN THE NATIONAL CAPITAL REGION

Christoph A. Vogel* and William R. Pendergrass
NOAA Atmospheric Turbulence and Diffusion Division, Oak Ridge, TN, U.S.A.

1. Introduction

The National Oceanic and Atmospheric Administration's UrbaNet program provides mean and turbulent data over selected urban environments to a variety of interested entities including federal and local emergency management agencies, operational forecasters, and atmospheric dispersion researchers. Recently a more formal testbed network of stations has been established in the Washington, DC area. A primary motivation in establishing the network was the lack of data at "neighborhood" spatial scales, and preliminary studies showing significant differences in wind vectors from established stations (often located at or near airports on the periphery of urban regions) and the downtown area.

Currently, each measurement station in the network consists of a 10 meter tower located on a rooftop with a propeller/vane anemometer, a sonic anemometer, and a naturally aspirated temperature and humidity sensor mounted at the top. Turbulent values from the sonic anemometer and mean values from the other two instruments are transmitted back to a NOAA server and placed in a database every 15 minutes. Currently there are 14 stations operational, with a cluster downtown and a wider spaced array in the surrounding area (Figure 1). This network of stations thus provides continuous mean and turbulence data at spatial scales much finer than is normally available.

2. Assessing persistence as a forecast for the wind vector field

A useful first-order tool for operational dispersion forecasting and modeling is the assessment of persistence forecasts of the discrete wind field. A method of quantifying the validity of persistence is through an autocorrelation analyses. The discrete autocorrelation (e.g., Press et al., 1989; Stull, 1988) can be expressed as:

*Corresponding author address: Christoph A. Vogel, NOAA/ATDD, P.O. Box 2456, Oak Ridge, TN 37831; e-mail: chris.vogel@noaa.gov.

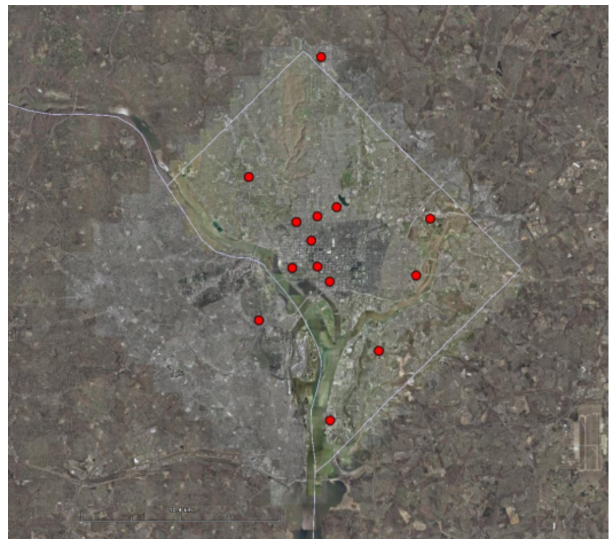

Figure 1: A map showing the UrbaNet testbed network locations in the National Capital Region.

$$r_{aa}(l) = \frac{\sum_{k=0}^{N-j-1} \left[\left(a_k - \bar{a}_k\right) \left(a_{k+j} - \bar{a}_{k+j}\right) \right]}{\sigma_k \; \sigma_{k+j}} \quad (1)$$

$$\sigma_k = \left[\sum_{k=0}^{N-j-1} \left(a_k - \bar{a}_k\right)^2 \right]^{1/2} \quad (2)$$

$$\sigma_{k+j} = \left[\sum_{k=0}^{N-j-1} \left(a_{k+j} - \bar{a}_{k+j}\right)^2 \right]^{1/2} \quad (3)$$

where the lag $l = j\Delta t; j = 0, \cdots, N/2.$

The autocorrelation function will give correlation values for the signal and a lagged version of itself (Figure 2). Of interest is determining a critical r_{aa} at a certain significance level, for a given wind component at a given station, so that a corresponding critical lag time can be determined. This critical lag time can then correspond to a time out to which a persistence forecast can be assumed useful. The method

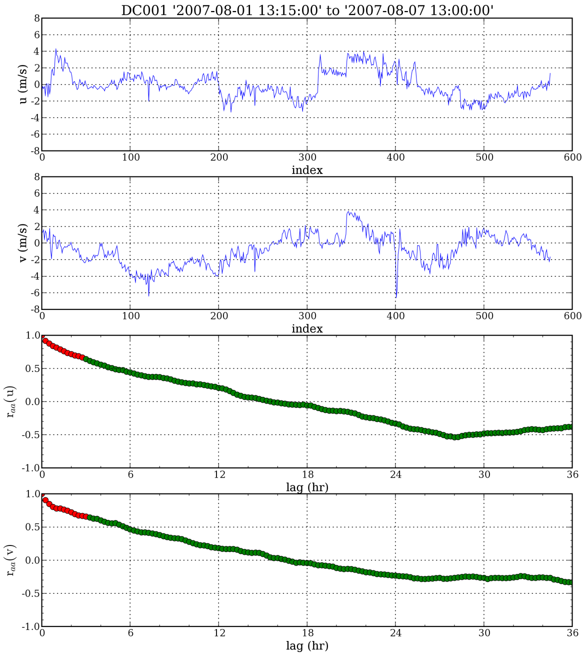

Figure 2: The north-south (u) and east-west (v) components of the wind and their associated autocorrelation functions for a six day period as measured at the Hoover Building (location DC001) in downtown Washington, DC. For this case, the computed critical correlation values gave critical lag times of 2.75 and 3.00 hours for the u and v components respectively. Only the correlation coefficients for the first 36 hours of lags are shown.

has been demonstrated for example by Gille (2005). A Gaussian distribution is assumed for a given block of wind data, and a critical r_{aa} magnitude is determined through:

$$r_c = \text{erf}^{-1}(c)\sqrt{\frac{2}{D}} \tag{4}$$

where r_c is a critical correlation coefficient, erf$^{-1}(c)$ is the inverse of the error function for a particular confidence level c, and D is a measure of the number of degrees of freedom (Bevington, 1969).

Because the autocorrelation function assumes *independent* (uncorrelated) values, which a time series of wind components is not, we define D in equation (4) as $D = N\Delta t/\tau$ were N is the number of points in the time series being analyzed, and τ is a decorrelation time scale. There can be different strategies in computing τ. Because of instances where the autocorrelation function could continue near zero without actually crossing zero (a common decorrelation criteria), this analysis chose the first

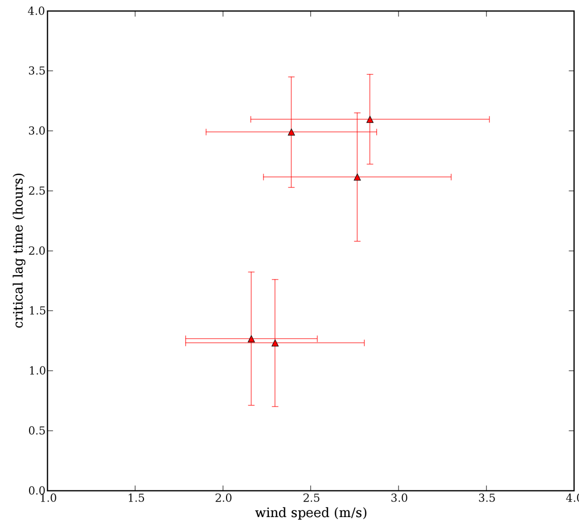

Figure 3: Critical lag times averages over the 14 sites shown in Figure 1 for five six-day blocks of data during the period 8 July 2007 to 7 August 2007. Error bars denote one standard deviation from the mean.

instance of a lag time to which the autocorrelation value dropped below the threshold $r_{aa} < 0.05$. So, for example, for a six day block of 15 minute average winds ($\Delta t = 0.25, N = 576$), if r_{aa} is less than 0.05 at a lag of 14 hours, $D = (576) \cdot (0.25)/(14) \approx 10$.

A thirty day mid-summer period was chosen to demonstrate the autocorrelation analysis. Fifteen minute wind component data from each measurement station were divided into five six-day blocks. Thus, five blocks for each of the 14 stations for both the u and v components, result in $5\times14\times2 = 140$ total autocorrelations performed. The computed critical lag times were averaged for each block and then averaged for both components as shown in Figure 3.

3. Discussion

The results of the analysis illustrated in Figure 3 show a range of approximately 1.0 to 3.0 hours for critical lag times, and hence times for which persistence forecasts could be considered valid. The mean of all 5 blocks is 2.24 hours. The data also fall in two distinct groups perhaps indicating two separate weather regimes. However, more robust analyses would need to be performed to make conclusive arguments on trends.

This brief analysis is an example of the type of tools that are being developed for operational use of the UrbaNet data. This particular analysis deserves more refinement especially in the averaging methods for the autocorrelations of the wind field, and in finding more objective means for determining D in equation (4). However, it is a useful first-order quantification of how long a persistence forecast for a discrete wind field could be considered valid.

References

Bevington, P. R., 1969: *Data Reduction and Error Analysis for the Physical Sciences*. McGraw-Hill, Inc.

Gille, S. T., 2005: *Lecture Notes: Statistical Methods for Environmental Sciences and Engineering*. Dept. of Mech. and Aero. Eng., UCSD.

Press, W. H., B. P. Flannery, S. A. Teukolsky, and W. T. Vetterling, 1989: *Numerical Recipes*. Cambridge University Press.

Stull, R. B., 1988: *An Introduction to Boundary Layer Meteorology*. Kluwer Academic Publishers.