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# ATMOSPHERIC STRUCTURE SIMULATION: AN AUTOREGRESSIVE MODEL FOR SMOOTH GEOPHYSICAL POWER SPECTRA WITH KNOWN AUTOCORRELATION FUNCTION

James H. Brown

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## Atmospheric Structure Simulation: An Autoregressive Model For Smooth Geophysical Power Spectra With Known Autocorrelation Function

#### **1. INTRODUCTION**

Atmospheric fluctuations in wind speed and gravity waves are characterized by continuous power spectral density functions. For example, one dimensional wind speed PSD's are found to have log-log slopes of about -5/3. Such spectra often are used in simulating an environment or predicting atmospheric structure. Fast Fourier transform analysis provides a means for filtering white noise with spatial filters to simulate a stationary time or spatial data set. In many applications the transform technique provides adequate processing speed. For example, repeatedly using the double precision IMSL routine DF2TCF,  $\epsilon = 00^\circ$ , point transform averages 6.91 ms on the Phillips Laboratory Convex model 210 computer. Geophysical data however, are multidimensional, and often exceed 1024 points. Three dimensional Fourier simulation of atmospheric structure that realistically allows for variable coherence length scales, RMS fluctuation levels, and spectral slopes would require months of execution time on a work station.

The Phillips Laboratory Strategic High Altitude Atmospheric Radiance Code (SHARC)<sup>1</sup> uses first principles to calculate point-to-space and limb viewing atmospheric background infrared radiance and transmittance. Real atmospheric infrared background perturbations occur from fluctuations in temperature and density of the contributing molecular species. Version 4 of the SHARC code envisions a capability to evaluate radiance structure from estimated variances in the standard temperature and density profiles. To provide a realistic but practical two-dimensional structure scene capability will require creative, efficient, and tested algorithms. The purpose of this report is to study the possibility of producing synthetic structure from autoregression analysis as contrasted with the common Fourier method with a view toward reducing the

Received for publication 4 February 1993

<sup>&</sup>lt;sup>1</sup>Sharma, R.D., et.al., (1991) Description of SHARC-2. The Strategic High Altitude Atmospheric Radiance Code, Phillips Laboratory technical report. PL-TR-91-2071. ADA 239008

computational burden. Only one-dimensional analysis is treated here but a subsequent report will present a two-dimensional approach.

#### 2. THEORY OF AUTOREGRESSIVE DIGITAL SPECTRAL ESTIMATION

This section is a brief review of autoregressive digital spectral estimation as presented by S. Lawrence  $Marple^2$  and Steven M. Kay<sup>3</sup>.

An autoregressive moving average (ARMA) model for a discrete time series, x(n), that approximates deterministic and stochastic processes can be represented by the filter linear difference equation:

$$x(n) = -\sum_{k=1}^{p} a(k) x(n-k) + \sum_{k=0}^{q} b(k) \varepsilon(n-k)$$

in which r(n) is the output sequence and  $\mathcal{E}(n)$  a white noise input driving sequence. The a(k) and b(k) coefficients form the autoregressive and moving average portions of the ARMA model respectively. A z transform analysis of the difference equation shows that the ARMA power spectral density (PSD) is:

$$P_{\text{ARMA}}(f) = T\rho_{w} \left| \frac{B(f)}{A(f)} \right|^{2}$$

where.

$$A(f) = 1 + \sum_{k=1}^{p} a(k) \exp(-2\pi i f kT)$$

and,

$$B(f) = 1 + \sum_{k=1}^{q} b(k) \exp(-2\pi i f k T).$$

T is the sampling interval and  $\rho_w$  is the variance of the white noise process. If all the moving average coefficients are zero, except b(0) = 1, then

$$x(n) = -\sum_{k=1}^{p} \alpha(k) x(n-k) + \varepsilon(n)$$

and the process is strictly autoregressive of order p. The autoregressive PSD becomes,

<sup>3</sup>Kay, Steven M., 1938 Modern Spectral Estimation, Theory & Application, Prentice-Hall, Englewood Cliffs, New Jersey.

<sup>&</sup>lt;sup>2</sup>Marple, S.L., 1987 Digital Spectral Analysis with Applications, Chapter 6, Prentice-Hall, Englewood Cliffs, New Jersey.

$$P_{AR}(f) = \frac{T\rho_{w}}{|A(f)|^2} = T \sum_{k=-\infty}^{\infty} r_{xx}(k) \exp(-2\pi i f kT)$$

where  $r_{XX}$  is the autocorrelation sequence at k and  $\rho_w$  is the variance of E(n). The relationship between the autocorrelation sequence and the pure autoregressive model is

$$r_{xx}(m) = \begin{cases} -\sum_{k=1}^{p} a(k)r_{xx}(m-k) & \text{for } m > 0\\ -\sum_{k=1}^{p} a(k)r_{xx}(-k) + \rho_{xy} & \text{for } m = 0\\ r_{xx}(-m) & \text{for } m < 0 \end{cases}$$

This expression may be evaluated for the p+1 lag indices  $0 \le \infty \le p$  by:

$$\begin{pmatrix} r_{\mathbf{xx}}(0) & r_{\mathbf{xx}}(-1) & \cdots & r_{\mathbf{xx}}(-p) \\ r_{\mathbf{xx}}(1) & r_{\mathbf{xx}}(0) & \cdots & r_{\mathbf{xx}}(a(1)) \\ \vdots & \vdots & \ddots & \vdots \\ r_{\mathbf{xx}}(p) & r_{\mathbf{xx}}(p-1) & \cdots & r_{\mathbf{xx}}(0) \end{pmatrix} \begin{pmatrix} 1 \\ a(1) \\ \vdots \\ a(p) \end{pmatrix} = \begin{pmatrix} \rho_{\mathbf{x}} \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

This expression forms the autoregressive Yule-Walker equations. Given the autocorrelation sequence for lags 0 to p, the autoregressive coefficients may be found from the above. Since  $r_{XX}(-k) = r^*_{XX}(k)$ , the autocorrelation matrix is both Toeplitz and Hermitian. A standard "Levinson" algorithm, which takes advantage of the Hermitian-Toeplitz matrix equation, was employed to solve for the AR parameters. The same Yule-Walker equations also occur if we attempt to solve the problem: find the "best", in a least square sense, set of equations that determine the coefficients

that predict 
$$\hat{\mathbf{X}}$$
 from  $\hat{x}(n) = -\sum_{k=1}^{p} a(k) x(n-k)$ , where  $\overline{(\hat{x}(n) - x(n))^2} = \rho_w$ . In summary, the Levinson

recursion computes sets of coefficients  $(a_1(1), \rho_1), (a_2(1), a_2(2), \rho_2), \dots, (a_p(1), a_p(2), \dots, a_p(p), \rho_p)$ where the final set at order p is the desired solution of the Yule-Walker expressions. For the AR(p) process,  $a_p(1) = a(i)$  for  $i = 1, 2, 3, \dots, p$  and  $\rho_p$  is the minimum prediction error, that is,  $\rho_w = \rho_p = \rho_{\min} = \xi [x^*(n](x[n] - \hat{x}[n])]$ . The algorithm is initialized by:

$$a_{1}[1] = -\frac{r_{xx}[1]}{r_{xx}[0]}$$
$$\rho_{1} = (1 - |a_{1}[1]|^{2})r_{xx}[0]$$

with the recursion for k = 2, 3, ..., p given by

З

$$r_{xx}[k] + \sum_{\substack{i=1\\j\in i}}^{k-1} a_{k-1}[\ell] r_{xx}[k-\ell]$$

$$a_k[k] = -\frac{\rho_{k-1}}{\rho_{k-1}}$$

$$a_k[i] = a_{k-1}[i] + a_k[k] a_{k-1}^*[k-i] \quad i = 1, 2, \dots, k-1$$

$$\rho_k = (1 - |a_k[k]|^2) \rho_{k-1}$$

The  $a_k[k]$  coefficients are known as reflection coefficients.

### 3. APPLICATION TO ATMOSPHERIC POWER SPECTRAL DENSITIES

Atmospheric power spectral density functions often are modeled by power law functions of the form  $^{4.5}$ 

$$PSD(k) = \frac{C}{\left(a^2 + k^2\right)^{v + \frac{1}{2}}}$$

The constant C is found from the definition that the total variance of the associated time series,  $\sigma^2$ , is equal to the area under the PSD<sup>6</sup>.

$$\sigma^{2} = 2 \int_{0}^{\infty} PSD(k) dk = 2C \int_{0}^{\infty} \frac{dk}{\left(a^{2} + k^{2}\right)^{\nu + \frac{1}{2}}} = 2C \frac{\sqrt{\pi}\Gamma(\nu)}{2a^{2\nu}\Gamma\left(\nu + \frac{1}{2}\right)}$$

so that the PSD model is

$$PSD(k) = \frac{\sigma^2 a^{2\nu} \Gamma\left(\nu + \frac{1}{2}\right)}{\sqrt{\pi} \Gamma(\nu) (a^2 + k^2)^{\nu + \frac{1}{2}}}$$

The relationship between the frequency domain PSD and the time or spatial domain autocorrelation function is specified by their Fourier transform pairs. Thus the autocorrelation function. (ACF), for the real even PSD function is

<sup>&</sup>lt;sup>4</sup>Tatarski, V.I., 1961 Wave Propagation in a Turbulent Medium, McGraw-Hill, .

<sup>&</sup>lt;sup>5</sup>Futterman, W.I., Schweitzer, E.L., and Newt, J.E. 1991 "Estimation of Scene Correlation Lengths", Characterization, Propagation, and Simulation of Sources and Backgrounds, *Proceedings SPIE* - The International Society of Optical Engineering, V1486, pp127-140, Orlando, Florida.

<sup>&</sup>lt;sup>6</sup>For the integral, see for example, Gradshteyn, I.S. and Ryzhik, I.M., 1965 Table of Integrals Series and Products, eq 3.241.4, Academic Press.

$$ACF(x) = IFFT(PSD) = 2\int_0^\infty \frac{\sigma^2 \Gamma\left(\nu + \frac{1}{2}\right) a^{2\nu} \cos(2\pi xk) dk}{\sqrt{\pi} \Gamma(\nu) \left(a^2 + k^2\right)^{\nu + \frac{1}{2}}}$$

The integral is evaluated using the Bessel function of the second kind of fractional order,  $K_{\rm V}$  to be?

$$ACF(x) = \frac{\sigma^2 2^{(1-\nu)} (2\pi a x)^{\nu} K_{\nu}(2\pi a x)}{\Gamma(\nu)}$$

Expressions for two and three dimensional power spectral densities can be evaluated from the model autocorrelation function by performing two and three dimensional Fourier transforms of ACF(x). For example, over the valid range for v, the two-dimensional isotropic power spectral density is

$$F(\bar{k}) = \frac{1}{(2\pi)} \iint \cos(\bar{k} \cdot \bar{r}) A C F(\bar{r}) d\bar{r}$$
$$F(f_k) = \frac{\sigma^2 v a^{2\nu}}{\pi (a^2 + f_k^2)^{\nu+1}}$$

while the three-dimensional isotropic power spectral density is

$$\Phi(\vec{k}) = \frac{1}{(2\pi)^3} \iiint \cos(\vec{k} \cdot \vec{r}) A C F(\vec{r}) d\vec{r}$$
$$\Phi(f_k) = \frac{\Gamma\left(\nu + \frac{3}{2}\right) \sigma^2 a^{2\nu}}{\pi \sqrt{\pi} \Gamma(\nu) \left(a^2 + f_k^2\right)^{\nu + \frac{3}{2}}}$$

The parameter "a" can be expressed in terms of the integral scale or equivalent width of the ACF. An equivalent width is defined as the area of a function divided by its central ordinate<sup>8</sup>, or

$$\frac{\int f(x)dx}{f(0)}$$

Thus the large scale correlation length  $L_c$  is defined by integrating ACF(x) over all positive values of x.

$$L_c = \frac{\int_0^{\infty} ACF(x) dx}{\sigma^2}$$

<sup>7</sup>Ibid., Eq & 32.5

<sup>8</sup>Bracewell, R.N., 1978 The Fourter Transform and Its Applications, McGraw-Hill, New York .

where  $\overline{\sigma}^2$  is the autocorrelation at zero separation. Observing that the equivalent width of a function is equal to the inverse of the equivalent width of its transform<sup>9</sup>, the correlation length mav Le written as

$$L_{c} \approx \frac{PSD(0)}{2\int_{0}^{\infty} PSD(k)dk} \approx \frac{PSD(0)}{2\sigma^{2}}$$

so that.

$$L_{c} = \frac{\sigma^{2} \Gamma\left(\nu + \frac{1}{2}\right) a^{2\nu}}{2\sigma^{2} \sqrt{\pi} \Gamma(\nu) a^{2\nu+1}} = \frac{\Gamma\left(\nu + \frac{1}{2}\right)}{2\sqrt{\pi} \Gamma(\nu) a} \quad or$$
$$a^{-1} = \frac{2\sqrt{\pi} \Gamma(\nu)}{\Gamma\left(\nu + \frac{1}{2}\right)} L_{c}$$

These relationships are visually compared in Figure 1. The upper left quadrant of the graph shows a log-log plot of the PSD function for a slope of -3,  $\sigma^2 = 0.2$ ,  $L_c = 5.0$  and a = 0.05. The upper right quadrant shows a linear plot of the PSD with  $L_c$  and  $\sigma^2$  calculated from the curve. The autocorrelation function is plotted in the lower left quadrant and also shows  $L_c$  and  $\sigma^2$  calculated from the curve. Quite obviously the parameter "a" depends upon the value of v, such that "a" coincides with the 'roll over" or "corner frequency" of the PSD. The correlation length, on the other hand, corresponds to a much higher frequency (and smaller PSD). As shown in the lower right quadrant of Figure 1, the parameter "a" assumes a value near the frequency of the peak power while  $1/L_c$  assumes a value on the far tail of the power curve.

#### IMPLEMENTATION

In practice a given power law PSD was constructed from the PSD and ACF models:

$$PSD(f) = \frac{\sigma_r^2 a^{2\nu} \Gamma(\nu + \frac{1}{2})}{\sqrt{\pi} \Gamma(\nu) (a^2 + f^2)^{\nu + \frac{1}{2}}} \approx \frac{2\sigma_r^2 \Delta x}{\left|1 + \sum_{i=1}^N a_i e^{j2\pi i \Delta x}\right|^2}$$
$$ACF(x) = \frac{\sigma^2 2^{(1-\nu)} (2\pi a x)^{\nu} K_{\nu}(2\pi a x)}{\Gamma(\nu)}$$

9<sub>Ibid</sub>

where,

 $\sigma_r^2 = residual error$   $\Delta x = spacing$   $a_i = model parameters$   $j \equiv \sqrt{-1}$ f = frequency (Hz)

Then, a spatial data sequence was simulated using a normally distributed set of pseudorandom numbers G(J). The simulation of M sequence values proceeded as follows: Set  $Y(1) = Y(2) = Y(3) = \cdots = Y(N) = 0$ . Then for J = N+1, N+2,  $\cdots$ , M+1000, create Y(J) from

 $Y(J) = G(J)\sigma_r - \sum_{l=1}^{N} a_l Y(J-l)$ . The simulated sequence is then contained in Y(1001), Y(1002), ...,

Y(M+1000).

After simulating such a discrete spatial sequence of a given PSD, the PSD of the simulated series was checked as follows. Using a forward and backward estimation method<sup>10</sup>, a set of NN  $b_i$  coefficients were found to estimate the simulated PSD from the formula.

$$PSD(f) = \frac{2\sigma_c^2 \Delta x}{\left|1 + \sum_{i=1}^{NN} b_i e^{j2\pi i \Delta x}\right|^2}$$

where  $\Delta x$  is the same spacing used to generate the synthetic series.

The forward and backward method solves the following least squares problem. Given M discrete series values Y(J), for J = 1, 2, ..., M, we find  $b_i$  values that minimize ERR, where,

$$ERR = \left(\sum_{J=NN+1}^{M} \left(Y(J) - \sum_{i=1}^{NN} b_i Y(J-i)\right)^2\right) + \left(\sum_{J=1}^{N-N} \left(Y(J) - \sum_{i=1}^{NN} b_i Y(J+i)\right)^2\right)$$

 $\sigma_c^2$  is then equal to  $\frac{ERR}{2(M-NN)}$ 

#### 5. RESULTS

<sup>10</sup> Haykin, Simon, ed., 1991 Advances in Spectrum Analysis and Array Processing. Vol.1. Prentice Hall. Englewood Cliffs New Jersey., pp.155-156.

The following discussion is aimed at producing a practical autoregressive model of atmospheric structure consistent with having a pre-assigned power spectral density and autocorrelation function. Correlation lengths and  $\sigma^2$  variances are taken from Strugala, et.al.<sup>11</sup>

Figure 2 shows an 8000 point sequence of Gaussian "white noise" having a spacing of 100 m, mean of zero, and standard deviation of 0.055. Figure 3 presents a histogram of the Gaussian data and Figure 4 shows the "flat" white noise spectra and associated autocorrelation function. The theoretical and calculated statistics agree, with the calculated having an average of 0.000117 and  $\sigma$  of 0.0549. Correlated sequences, histograms, PSD's and ACF's of subsequent plots may be compared to this "unfiltered sequence."

Figure 5 is typical of all the plots in this report showing log-log PSD's in the left panel and ACF's in the right panel. This and subsequent plots have PSD's measured in  $\frac{(\delta \text{ Temperature}/\text{ Temperature})^2}{\text{Wavenumber}}$  and wavenumber measured in km<sup>-1</sup>. Three curves usually appear in

each panel. The solid unmarked curves are the "theoretical" or inputted PSD or ACF. The curves marked by an  $\mathbf{X}$  are the autoregressive predicted PSD's and ACF's, and the curves marked by an open square are PSD's and ACF's derived from the simulated data sequences. Except where otherwise noted, the data spacing is 100 m and the Nyquist frequency is 5 km<sup>-1</sup>. The input parameters for Figure 5 are  $L_c = 1.75$  km,  $\sigma^2 = 0.00102$ , spectral slope (S) = -5/3. Using six linear predictor coefficients, the predicted values are  $L_c= 1.44$  km from the PSD and 1.50 km from the ACF, and  $\sigma^2 = 0.00107$  from the area of the PSD. Using 12 coefficients to determine the simulated results, the values for the simulated curves are  $L_c = 1.38$  km from the PSD and 1.44 km from the ACF, and  $\sigma^2 = 0.00106$  from the area of the PSD. Visually examining Figure 5, clearly shows that using 6 coefficients for the predictor and 12 coefficients for the simulated values reproduces the theoretical slope quite well except at the highest wavenumbers. Also, at low wavenumbers, the predicted and simulated PSD's show a -16 percent DC bias from the theoretical. Part of the high wavenumber divergence is due to the sharpness of the autocorrelation function at zero lag. In fact, for the specified input spectral slope of -5/3, a sharp cusp exists at zero lag. This cusp introduces an error into the estimate of the linear prediction coefficients that affect the PSD at high wavenumbers. To test this hypothesis, the first value of the autocorrelation function at zero lag was modified by setting it equal to a value linearly extrapolated from the second and third values. This modification led to the curves in Figure 6. Here we see much better agreement between the theoretical and modeled curves at high wavenumbers and improvement at low wavenumbers. Improvement in the spectral parameters is also evident.  $L_c$  improves to 1.54 km for the predicted PSD and 1.60 km for the predicted ACF. Figure 7 shows a sequence of 8000 data points simulated over 800 km. When compared with Figure 2, the -5/3 spectral filtering is obvious. To see if the simulated data retains the Gaussian PDF, a histogram of the simulated data is examined in Figure 8. The figure shows that the variance of the simulated data = 0.00102, matching the input parameter,  $\sigma^2$ . Also, the histogram closely follows the shape of the theoretical PDF as shown by the solid curve. The effects of using more or fewer predictor coefficients are shown in Figures 9

<sup>&</sup>lt;sup>11</sup>Strugala, L.A., Newt, J.E., Futterman, W.I., Schweitzer, E.L., Herman, B.J., and Sears, R.D. 1991 Development of High Resolution Statistically Non-stationary Infrared Earthlimb Radiance Scenes, *Characterization, Propagation, and* Simulation of Sources and Backgrounds, Proceedings SPIE - The International Society for Optical Engineering, V1486, pp 176-187, Orlando, Fiorida.

and 10. Figure 9 is calculated for only one predictor coefficient while Figure 10 is calculated using 20 predictor coefficients. Except for the bias at low wavenumbers, using only one coefficient for the predictor does remarkably well for the specified input parameters. However, with the use of 20 coefficients, any difference between the theoretical, predicted, and simulated curves is practically erased. Resultant values for the predicted and simulated spectral parameters also improve. For example,  $L_c$  improves to 1.63 km for the simulated PSD and 1.70 km for the simulated ACF. Figure 11 provides a visual perspective of how the 20 corresponding reflection coefficients decrease as a function of reflection coefficient number. Ordinarily, the reflection coefficient was mentioned above causes the second reflection coefficient to dip below the smooth value. Evidently this helps compensate for the cusp in the ACF.

One may see the effects of increasing the value of the correlation length  $L_c$ , in Figures 12-14. These curves are calculated for  $L_c = 10$  km,  $\sigma^2 = 0.0049$ , and S = -5/3. Using 6 coefficients for the predicted PSD and 12 coefficients for the simulated PSD, produces the curves of Figures 12 and 13. Figure 12 illustrates the increased difficulty in simulating a PSD and ACF having a large  $L_c$  with a small number of coefficients. Figure 13 clearly shows the effect of the larger correlation length on the simulated spatial sequence. As expected, greater smoothing (data correlation) results from using the larger scale size. Figure 14 illustrates the improvement in the predicted and simulated PSD and ACF by using 20 predictor coefficients for both the predicted and simulated curves.

Figures 15-20 show the result of repeating the calculations for a spectral slope of -2. Figures 15-17 have inputted spectral parameters of  $L_c = 1.75$  and  $\sigma^2 = 0.00102$  while Figures 18-20 have  $L_c = 10$  and  $\sigma^2 = 0.0049$ . For a slope of -2, using  $\epsilon$  coefficients for the predicted PSD and 12 coefficients for the simulated PSD, gives good agreement between theoretical, predicted, and simulated curves, even for  $L_c = 10$ . For a theoretical  $L_c = 1.75$ ,  $\sigma^2 = 0.00102$ , the predicted values are  $L_{c}=1.73$  from the PSD and 1.75 from the ACF, and  $\sigma^{2}=0.00104$  from the area of the PSD. The values for the simulated curves are  $L_c = 1.65$  from the PSD and 1.67 from the ACF, and  $\sigma^2 =$ 0.00103 from the area of the PSD. Figure 16 shows the sequence of 8000 data points simulated over 800 km for the -2 spectral slope and  $L_c = 1.75$ . When this result is compared with Figure 7, the increased filtering is evident. Again the simulated data retains the Gaussian PDF as shown in the histogram of Figure 17. The figure shows that the variance of the simulated data = 0.00102, matching the input parameter,  $\sigma^2$ . As shown in Figure 18, inputting a theoretical L<sub>c</sub>= 10 and  $\sigma^2$  = 0.0049 gives the predicted values of L<sub>c</sub>= 9.98 from the PSD and 10 from the ACF, and  $\sigma^2$  = 0.00491 from the area of the PSD. The values for the simulated curves are  $L_c$ = 9.37 from the PSD and 9.39 from the ACF, and  $\sigma^2 = 0.00472$  from the area of the PSD. Figure 19 shows the sequence of 8000 data points simulated over 800 km for the -2 spectral slope and  $L_c$ = 10. Figure 20 again shows that the histogram of the simulated data retains the Gaussian PDF and that the variance of the simulated data = 0.00468, approximating the input parameter,  $\sigma^2$ .

Figure 21 repeats the calculations for a theoretical spectral slope of -3,  $L_c= 1.75$ , and  $\sigma^2 = 0.00102$ . Up to this point the autocorrelation function has been modified at zero lag as discussed above. However, as evident in Figure 21, for slopes of -2 and greater, the modified ACF results in a divergence of the predicted PSD at high wavenumbers whereas the unmodified ACF produces

good fidelity at high wavenumbers. For this reason, use of the modified ACF is appropriate only for the -5/3 spectral slope. For slopes of -2 and larger, subsequent analysis will use the unmodified ACF exclusively.

Figures 22-27 show the result of repeating the calculations for a spectral slope of -3. Figures 22-24 have inputted spectral parameters of  $L_c = 1.75$  and  $\sigma^2 = 0.00102$  while Figures 25-27 have  $L_c \approx 10$  and  $\sigma^2 = 0.0049$ . For a slope of -3, using 6 coefficients for the predicted PSD and 12 coefficients for the simulated PSD, good agreement obtains between theoretical, predicted, and simulated curves, although there is less agreement at low wavenumbers for  $L_c = 10$ . For a theoretical  $L_c = 1.75$ ,  $\sigma^2 = 0.00102$ , the predicted values are  $L_c = 1.88$  from the PSD and 1.88 from the ACF, and  $\sigma^2 = 0.00102$  from the area of the PSD. The values for the simulated curves are L<sub>c</sub>= 1.79 from the PSD and 1.79 from the ACF, and  $\sigma^2 = 0.00102$  from the area of the PSD. Figure 23 shows the sequence of 8000 data points simulated over 800 km for the -3 spectral slope and  $L_{c}$ = 1.75. Comparisons with Figure 16 show the -3 versus -2 increased filtering. Again the simulated data retains the Gaussian PDF as shown in the histogram of Figure 24. The figure shows that the variance of the simulated data = 0.00102, matching the input parameter,  $\sigma^2$ . As shown in Figure 25, inputting a theoretical  $L_c=10$  and  $\sigma^2=0.0049$ , gives predicted values of  $L_c=16.6$  from the PSD and 16.6 from the ACF, and  $\sigma^2 = 0.00490$  from the area of the PSD. The values for the simulated curves are  $L_c = 16.1$  from the PSD and 16.1 from the ACF, and  $\sigma^2 = 0.00473$  from the area of the PSD. Figure 26 shows the sequence of 8000 data points simulated over 800 km for the -3 spectral slope and  $L_c=$  10. Figure 27 again shows that the histogram of the simulated data retains the Gaussian PDF and that the variance of the simulated data = 0.00471, approximating the input parameter  $c^2$  Figure 28 shows the improvement that is made by using 12 predictor coefficients. In this case, the predicted values are  $L_c=$  13 from the PSD and 13 from the ACF, and  $\sigma^2 = 0.00490.$ 

The final spectral slope examined in this report is for a slope = -4. Figures 29-34 present the results of repeating the calculations for a S = -4. Figures 29-31 have inputted spectral parameters of  $L_c = 1.75$  and  $\sigma^2 = 0.00102$  while Figures 32-34 have  $L_c = 10$  and  $\sigma^2 = 0.0049$ . In this case, using 6 coefficients for the predicted PSD and 12 coefficients for the simulated PSD yields good agreement between theoretical, predicted, and simulated curves. For a theoretical  $L_{c}$ = 1.75,  $\sigma^{2}$  = 0.00102, the predicted values are  $L_c$  = 1.75 from the PSD and 1.75 from the ACF, and  $\sigma^2$  = 0.00102 from the area of the PSD. The values for the simulated curves are  $L_c = 1.67$  from the PSD and 1.67 from the ACF, and  $\sigma^2 = 0.00102$  from the area of the PSD. Figure 30 shows the sequence of 8000 data points simulated over 800 km for the -4 spectral slope and  $L_c= 1.75$ . Comparisons with Figure 23 show the -4 versus -3 increased filtering effect. Again the simulated data retains the Gaussian PDF as shown in the histogram of Figure 31. The figure shows that the variance of the simulated data = 0.00102, matching the input parameter,  $\sigma^2$ . As shown in Figure 32, inputting a theoretical  $L_c = 10$  and  $\sigma^2 = 0.0049$ , gives predicted values of  $L_c = 9.98$  from the PSD and 9.98 from the ACF, and  $\sigma^2 = 0.00490$  from the area of the PSD. The values for the simulated curves are  $L_c = 10.1$  from the PSD and 10.1 from the ACF, and  $\sigma^2 = 0.00463$  from the area of the PSD. Figure 33 shows the sequence of 8000 data points simulated over 800 km for the -4 spectral slope and  $L_c= 10$ . Figure 34 again shows that the histogram of the simulated data retains the Gaussian PDF and that the variance of the simulated data = 0.00461, approximating the input parameter,  $\sigma^2$ .

Up to this point the analysis has been based on a data spacing of 100 m. The effect of doubling the spacing is demonstrated in Figures 35 and 36. These plots have inputted spectral parameters of S = -5/3 and  $L_c = 5$ . Figure 35, which was calculated for a data spacing of 200 m, may be compared with Figure 36 which has a data spacing of 100 m. Of course, doubling the data spacing from 100 to 200 m halves the spatial resolution and reduces the Nyquist frequency from 5 km<sup>-1</sup> to 2.t km<sup>-1</sup>. If reducing resolution is acceptable, the positive effect is the improvement in the predicted correlation length. For example, by using 6 linear predictor coefficients, the predicted  $L_c = 3.6$  km for a spacing of 100 m but  $L_c = 4.28$  km for a spacing of 200 m.

#### 6. CONCLUSION

Geophysical phenomena within a specified domain often are characterized by smooth continuous power spectral densities having a negative power law slope. The association of one-, two-, and three-dimensional geophysical spectral densities with a given autocorrelation function was reviewed and the autoregressive methods of modern spectral estimation were explored. An autoregressive alternative to the more common Fourier transform analysis was studied with a goal of reducing the enormous computational burden of generating synthetic structure scenes from Gaussian random number sets. A 6 coefficient AR run to simulate 1300 points, using the Fhillips Laboratory model 210 Convex computer, showed an average execution time of 0.462 ms, an improvement of a factor of 6.91/0.462 over the fast Fourier transform. In generating twodimensional synthetic arrays, greater savings would result due to the 8-fold symmetry of the quarter-plane AR coefficients. It was demonstrated how the resolution and accuracy of predicted and simulated data, their PSD's and ACF's, and their parameters, change with spectral slope. correlation length, data spacing, and prediction order. In particular, six linear prediction coefficients are all that is necessary in many cases to generate a synthetic spatial sequence that retains a specified power law, correlation scale, variance, and probability distribution function. For a desired spectral slope of -5/3 one should employ an autocorrelation function having a modified zero lag value. For an equal linear predictor order, structured data having smaller correlation length, larger spectral slope, or reduced data resolution, have greater fidelity to specified characteristics than those generated for small slope, larger correlation length, or higher resolution. However, fidelity often can be reestablished by increasing the spectral order from 6 coefficients to 12 or in the worst case 20 coefficients. Since the maximum vertical correlation length over relevant SHARC altitudes is reported to be approximately 10 km, a vertical resolution of 100 m can be achieved with a minimum of coefficients. However, since maximum horizontal correlation lengths are reported to be approximately 85 km, horizontal resolution must be sacrificed or else many more coefficients must be used to achieve fidelity at both low and high frequencies. Where low frequency simulation is unimportant, one may retreat to a minimum number of coefficients and still achieve fidelity at mid and high frequencies.

Autoregressive (AR) and autoregressive moving average (ARMA) modeling should be considered in creating large atmospheric structured scenes. A subsequent report will address the potential for using two-dimensional ARMA modeling to generate two and three-dimensional structured scenes.







ALMBER OF VRLUES IN PSG 4096

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Figure 3. Histogram of sample Gaussian random number sequence. Theoretical mean = 0., theoretical S.D. = 0.055.





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Figure 5. Left panel, theoretical PSD input (uninarked), autoregressive predictor PSD (marked by x), and simulated PSD (marked by small square). Right panel, corresponding autocorrelation functions.  $L_c = 1.75$  km, log-log spectral slope = -5/3,  $\sigma^2$ = 1.02E-03, spacing = 100 m. Unmodified theoretical autocorrelation function. Six predictor coefficients. NUMBER OF VALUES IN PSC-4036 THIS IS FILE SIMIB 14-DEC-92 SIMULATE DATA WITH SECD=3333 NUMBER OF POINTS SIMULATED-HOUDO OUTPUT FROM PROCRAM MODELI 14-DEC-92

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Left panel, theoretical PSD input (unmarked), autoregressive predictor PSD (marked by x), and simulated PSD (marked by small square). Right panel, corresponding autocorrelation functions.  $L_c = 1.75$  km, S = -5/3,  $\sigma^2 = 1.02E-03$ , spacing = 100 m. Theoretical autocorrelation function modified at lag = 0. Six predictor coefficients Figure 6.

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= 1.02E-03d 5 Figure 7. Autoregressive simulated structure sequence.  $L_c = 1.75$  km, S = -5/3,

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Figure 11. Plot of the square of the reflection coefficient versus reflection coefficient number for twenty reflection coefficients.  $I_{c} = 1.75 \text{ km}$ , S = -5/3,  $\sigma^{2} = 1.02E-03$ , spaining = 100 m. The reficial autocorrelation function modified at lag = 0

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Figure 12. Left panel, theoretical PSD input (unmarked), autoregressive predictor PSD (marked by x), and simulated PSD (marked by small square). Right panel, corresponding autocorrelation functions.  $L_c = 10$  km, S = -5/3,  $\sigma^2 = 4.9E-03$ , spacing = 100 m. Theoretical autocorrelation function modified at lag = 0. Six predictor coefficients

USE MODIFIED AUTOCORRELATION THIS IS FILE STMIE IS-DEC-92 SIMULATE CATA 41TH SEED=3333 NUMBER OF POINTS SIMILATED=800000 NUMBER OF VALUES IN PSD=4096 OUTPUT FROM FROMPHONEL IS-DEC-92

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Figure 14. Left panel, theoretical PSD input (unmarked), autoregressive predictor PSD (marked by x), and simulated PSD (marked by small square). Right panel, corresponding autocorrelation functions.  $L_c = 10$  km, S = -5/3,  $\sigma^2 = 4.9E-03$ , spacing = 100 m. Theoretical autocorrelation function modified at lag = 0. Twenty predictor coefficients





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THIS IS FILE STHIB 14-DEC-92 STHULATE DATA HITH SEED#3333 NUMBER OF POINTS STHULATED+80000 NUMBER OF VALUES IN PSD+4096 OUTPUT FROM PROCRAM HODELIA 14-DEC-97 PREDICTOR WAS ESTIMATED FROM PSD MODEL LC= 1.75E+00 STOMA#42 1.02E-03 SLOPE-0F PSD+2.00 SPACING= 1.00E-01 A= 9.09E-02 ALL AREA'S OF PSD RAE CORRECTED FOR VALUES RADVE NYGUIST FREQUENCY OF 5.00E+00 IS 1.19E-05 VALLES FROM DRICINAL, AREA OF PSD= 1.02E-03 LC FROM PSD= 1.75E+00 AREA OF AUTOCORRELATION= 3.60E-03 LE FROM AUTOCORRELATION= 1.75E+00 VALUES FROM DRICINAL, AREA OF PSD= 1.02E-03 LC FROM PSD= 1.75E+00 AREA OF AUTOCORRELATION= 3.60E-03 LE FROM AUTOCORRELATION= 1.75E+00 VALUES FROM PREDICTOR.AREA OF PSD= 1.04E-03 LC FROM PSD= 1.75E+00 AREA OF AUTOCORRELATION= 3.50E-03 LE FROM AUTOCORRELATION= 1.75E+00





NUMBER OF VALUES IN PSD=4096 THIS IS FILE SIMIR 14-DEC-92 SIMULATE DATA WITH SEED.#3333 NUMBER OF POINTS SIMULATED=B0000 OUTPUT FROM PROGRAM MODELIA 14-DEC-92

PREGICTOR MAS ESTIMATED FROM PSD MODEL LC= 1.756.00 SICMA#Z 1.02E-03 SLOPE DF PSD-2.00 SPACINC= 1.00E-01 A= 9.09E-02 ALL AREA'S 0° PSD ARE CORRECTED FOR VRLUES ARCVE NYOUTST FREQUENCY OF 5.00E.00 IS 1.19E-05 VALUES FROM DRICHAL, AREA OF PSD= 1.02E-03 LC FROM PSD= 1.75E.00 AREA OF FUTOCORRELATION= 3.60C-03 LC FROM AUTOCORRELATION= 1.75E.00 VALUES FROM PRECICTOR.AREA OF PSD= 1.04E-03 LC FROM PSD= 1.73E.00 AREA OF AUTOCORRELATION= 3.60C-03 LC FROM AUTOCORRELATION= 1.75E.00





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NUMBER OF VRLUES IN PSD=4095 THIS IS FILE SIMIR 15-DEC-92 SIMULDIE DATA HITH SEEU 3333 NUMBER OF POINTS STRUCATED+80000 OUTPUT FROM PROCREM MODEL,1 15-DEC-92 USE NORMAL RUTOCORRELATION

6 Sec.

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PREDICTOR MAS ESTIMATED FROM PSO MODEL LC= 1,000 401 SIGMARX2 4,90E-03 SLOPE OF PSD=2,00 SPACT 1,00E-01 A= 1,55E-02

ALL AREA'S OF PSO ARE CORRECTED FOR VRLUES ABOVE NYOUTST FREAUENCY OF SLOGFOD IS 9.93E-OG VPLUES FROM DRIGIANL, RUEA OF PSOL 4.90E-03 LC FROM PSOL 1.00E+01 AREA OF RUTOCORRELATION= 9.60E-02 LC FROM AUTOCORRELATION= 1.00E+01 VPLUES FROM PREDICTOR AREA OF PSOL 4.90E-03 LC FROM PSOL 9.90E+00 AREA OF AUTOCORRELATION= 9.60E-02 LC FROM AUTOCORRELATION= 1.00E+01 VPLUES FROM SIMULATED AREA OF PSOL 4.77E-03 LC FROM PSOL 9.37E+00 AREA OF AUTOCORRELATION= 9.60E-02 LC FROM AUTOCORRELATION= 1.00E+01 VPLUES FROM SIMULATED AREA OF PSOL 4.77E-03 LC FROM PSOL 9.37E+00 AREA OF AUTOCORRELATION= 8.64E-02 LC FROM AUTOCORRELATION= 8.39E+00



Figure 18. Left panel, theoretical PSD input (unmarked), autoregressive predictor PSD (marked by x), and simulated PSD (marked by small square). Right panel, corresponding autocorrelation functions.  $L_c = 10 \text{ km}$ , S = -2,  $\sigma^2 = 4.9E-03$ , spacing = 100 m. Unmodified theoretical autocorrelation function. Six predictor coefficients



PREDICTOR MAS EST THATED FROM PSD HOBEL LC- 1.00E.01 SIDMA+2 4.90E-03 SLOPE OF PSD-2.00 SPACINGA 1.00E OI A 1.59E-02 ALL AREA'S OF PSD ARE CORRECTED FOR VALUES RUOVE NYOUIST FREQUENCY OF 5.00E+00 IS 9.93E-06 VALUES FROM CHICHMAL, AREA OF PSD- 4.90E-03 LC FROM PSD- 1.00E+01 AREA OF RUICOCRRELATION= 9.80E-02 LC FROM PUTCOCRRELATION= 1.00E+01 VALUES FROM PREDICTOR.AREA OF PSD- 4.91E-03 LC FROM PSD- 1.00E+01 AREA OF AUTOCORRELATION= 9.80E-02 LC FROM PUTCOCRRELATION= 1.00E+01 AVERACE= 2.216-03 ESTIMATED VARIANCE= 4.68E-03





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USE NORMER AUTOCCRRELATION THIS IS FILE SIMIB IS-OEC-32 SIMULATE DATA WITH SEED-3373 NUMBER OF POINTS SIMULATED-B00000 · NUMBER OF VALUES IN PSD-4095 OUTPUT FROM PROCRAM MODELT IS-DEC-92

PREDICTOR WAS ESTIMATED FROM FSD HOLEL LE= 1.006+01 SICH##2 4.90E-03 SLOPE OF PSD=2.00 SPACING= 1.00E-01 R= 1.55E-02 ALL AREA'S OF PGD ARE CORRECTED FOR VALUES PROVE NYAUTST FREQUENCY OF 5.00E+00 IS 9.93E-05 VALUES FROM ORTCOMAL, AREA OF PSD= 4.90E-03 LC FROM PSD= 1.00E+01 AREA OF AUTOCORRELATION± 9.80E-05 LC FROM AUTOCORRELATION= 1.00E+01 VALUES FROM AREDICTOR.AREA OF PSD= 4.91E-03 LC FROM PSD= 9.99E+00 AREA OF AUTOCORRELATION± 9.80E-02 LC FROM AUTOCORRELATION= 1.00E+01 VALUES FROM AREDICTOR.AREA OF PSD= 4.91E-03 LC FROM PSD= 9.99E+00 AREA OF AUTOCORRELATION± 9.80E-02 LC FROM AUTOCORRELATION= 1.00E+01





NUMBER OF VALUES IN FED-4098

SPACING- 1.00E-01 R. 1.45E-01 5.00E+00 IS 4 17E-07 THIS IS FILE SIMIE 14-DEC-92 SIMULATE DATA WITH SEED+3933 MUMBER DF POINTS SIMIKATED 00000 GUTPUT FROM PROCRAM MEDELI 14-DEC-92 PREDICTOR WAS ESTIMATED FROM PSD MEDEL LC= 1 75E400 SICMARK2 1.02E-03 SI OPE OF P5D=3.00 SPA RLL RAER'S OF PSD RAE CORRECTED FOR VRLUES ABOVE NYOUIST FREDUENCY OF 5.00E+00 IS 4 17E-07



33

Figure 21. Left panel, theoretical PSD input (unmarked), autoregressive predictor PSD (marked by x), and simulated PSD (marked) by small square). Right panel, corresponding autocorrelation functions.  $L_c = 1.75$  km, S = -3,  $\sigma^2 = 1.02E-03$ , spacing = 100 m. Theoretical autocorrelation function modified at lag = 0. Six predictor coefficients THIS IS FILE SIMIN 14-DEC-92 SIMULATE DATA WITH STUD-4000 NUMBER OF POINTS SIMULATED-E0000 NUMBER OF VICLES IN PSD-4096 OUTPUT FROM PROCRAM MODELLA 14-DEC-92

PREDICTOR UNS ESTIMATED FROM PSO MODEL LC= 1.75E+00 STGMM=Z 1.02E-03 SLOPE OF PSO.3.00 SPACIND= 1.00E-01 A= 1.43E-01 ALL DREATS OF PSO ARE CORRECTED FOR VALUES ABOVE NYOUIST FREQUENCY OF SLODE+00-15 4.17E-07 VALUES FROM ORIGINAL, ARED OF PSO= 1.02E-03 LC FROM PSO= 1.75E+00 AREA OF AUTOCORRELATION - 3.54E-03 LC FROM AUTOCORRELATION - 1.73E+00 VALUES FROM PREDICTOR.AREA FF PSO= 1.02E-03 LC FROM PSO= 1.98E+00 AREA OF AUTOCORRELATION - 3.54E-03 LC FROM AUTOCORRELATION - 1.73E+00 VALUES FROM SIMULATED AREA FF PSO= 1.02E-03 LC FROM PSO= 1.79E+00 AREA OF AUTOCORRELATION - 3.54E-03 LC TOM AUTOCORRELATION - 1.73E+00 VALUES FROM SIMULATED AREA FF PSO= 1.02E-03 LC FROM PSO= 1.79E+00 AREA OF AUTOCORRELATION - 3.55E-03 LC TOM AUTOCORRELATION - 1.73E+00 VALUES FROM SIMULATED AREA FF PSO= 1.02E-03 LC FROM PSO= 1.79E+00 AREA OF AUTOCORRELATION - 3.55E-03 LC TOM AUTOCORRELATION - 1.73E+00



Left panel, theoretical PSD input (unmarked), autoregressive predictor PSD (marked by x), and simulated PSD (marked by small square). Right panel, corresponding autocorrelation functions.  $L_c = 1.75$  km, S = -3,  $\sigma^2 = 1.02E-03$ , spacing = 100 m. Unmodified theoretical autocorrelation function. Six predictor coefficients Mgure 22.

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THIS IS FILE STHLE ALOEC-92 STMULATE DATA WITH SEED-3333 NUMBER OF POINTS STMLLATED-BCOOCI NUMBER OF VALUES IN PSD-4096 OUTOUT FROM PROFEME HODELIN 14-06C-92 PREDICTOR MPS ESTIMATED FROM PSD HODEL LC= 1.75E+00 SICMR#Z 1.02E-03 SLOPE OF PSD=3.00 SPACING= 1.90E-01 A= 1.43E-01 ALL AREA'S OF PSD ARE CORRECTED FOR VALUES TREQUENCY OF 5.00E-00 IS 4.17E-07 ALL AREA'S OF PSD ARE CORRECTED FOR VALUES TREQUENCY OF 5.00E-00 IS 4.17E-07 VALUES FROM CRIGINAL, AREA OF PSD= 1.02E-03 LL FROM PSD=1.13E+00 REA OF ANTOCORRELATION= 3.54E-03 LL FRUM AUTOCORRELATION= 1.56E+00 VALUES FROM PREDICTOR AREA OF PSD=1.02E-03 LL FROM PSD=1.13E+00 REA OF ANTOCORRELATION= 3.54E-03 LL FRUM AUTOCORRELATION= 1.66E+00 VALUES FROM PREDICTOR AREA OF PSD=1.02E-03 LL FRUM PSD=1.13E+00 REA OF ANTOCORRELATION= 3.54E-03 LL FRUM AUTOCORRELATION= 1.66E+00 VALUES FROM PREDICTOR AREA OF PSD=1.02E-03 LL FRUM FSD=1.03E+00 REA OF ANTOCORRELATION= 3.64E-03 LL FRUM AUTOCORRELATION= 1.66E+00 VALUES FROM PREDICTOR AND A PSD=1.02E-03 LL FRUM FSD=1.03E+00 REA OF ANTOCORRELATION= 3.64E-03 LL FRUM AUTOCORRELATION= 1.66E+00 VALUES FROM PREDICTOR PRED-1.02E-03 LL FRUM FSD=1.03E+00 REA OF ANTOCORRELATION= 3.64E-03 LL FRUM AUTOCORSELATION= 1.66E+00 VALUES FROM PREDICTOR PRED-1.02E-03 LL FRUM FSD=1.03E+00 REA OF ANTOCORRELATION= 3.64E-03 LL FRUM AUTOCORSELATION= 1.66E+00 VALUES FROM PREDICTOR PRED-1.02E-03 LL FRUM FSD=1.02E-03 LL FRUM AUTOCORSELATION= 1.66E+00





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THIS IS FILE STHIB 14-DEC-92 STHULATE DATA WITH SEED-3733 NUMBER OF PRINTS STHULATED-BODDO - NUMBER OF VALUES IN PSD-4096 GUTPUT FROM PROGRAM MODELIA 14-DEC-92 PREDICTOR MAS ESTIMATED FROM PSD MODEL LE= 1.756+00 STATAM\_Z 1.026-03 SLDME DF PSO-3.00 STATANG= 1.006-01 AL 1.436-01 AL AREN'S OF FORMEL AREN PSD MODEL LE= 1.756+00 STATAM\_Z 1.026-03 SLDME DF PSO-3.00 STATANG= 1.006-01 AL 1.436-01 AL AREN'S OF FORMEL AREN PSD MODEL LE= 1.756+00 STATAM\_Z 1.026-03 SLDME DF PSO-3.00 STATANG= 1.006-01 AL 1.436-01 VALLES FROM PREDICTOR AREN DF PSD-1.026-03 LC FROM PSD-1.756+00 AREN DF PALOCORRELATION-3.546-03 LC FROM AUTOCORRELATION-1.736+00 VALLES FROM PREDICTOR.7866 DF PSD-1.026-03 LC FROM PSD-1.086-00 AREN DF AUTOCORRELATION-3.546-03 LC FROM AUTOCORRELATION-1.266+00 VALLES FROM PREDICTOR.7866 DF PSD-1.0276-03 LC FROM PSD-1.086+00 AREN DF AUTOCORRELATION-3.546-03 LC FROM AUTOCORRELATION-1.266+00



Figure 24. Histogram of autoregressive simulated structure sequence.  $L_c = 1.75$  km, S = -3,  $\sigma^2 = 1.02$ E-03

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USE NORMAL AUTOCORRELATION

NUMBER OF VALUES IN PSD-4095 THIS IS FLEE STMAB IS-DEC-92 STMMATE DATA ULTA SENDI3333 NUMBER OF POINTS SIMULATED-E0000 OMIFMET FROM PROMOM MODELL IS-DEC-92





Left panel, theoretical PSD input (unmarked), autoregressive predictor PSD (marked by x), and simulated PSD (marked by small square). Right panel, corresponding autocorrelation functions.  $L_c = 10$  km, S = -3,  $\sigma^2 = 4.9E-03$ , spacing = 100 m. Unmodified theoretical autocorrelation function. Six predictor coefficients Figure 25.



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PHEDICION HAS ESTIMATED FROM PSO MODEL LC# 1.006+01 SIGMA#X2 4.906-03 SLOPE OF PSO -3.00 SPHCING# 1.006-01 A# 2.506-02 ALL ARFA'S OF PSO ARE COMRECTED FOR VALUES RUDVE INCUTST FRECKENCY OF 5.006+00 IS 6.12E-08 VALUES FROM ORIGINAL, ARFA OF PSO: 4.90E-03 LC FROM PSO: 1.00E+01 ARFA OF AUTOCORRELATION. 9.29E-02 LC FROM AUTOCOMRELATIONE 9.99E+03 VALUES FROM PREDICTOR.AREA OF PSO: 4.90E-03 LC FROM PSO: 1.00E+01 ARFA OF AUTOCORRELATION. 9.29E-03 LC FROM AUTOCOMRELATIONE 9.99E+03 VALUES FROM PREDICTOR.AREA OF PSO: 4.90E-03 LC FROM PSO: 1.00E+01 ARFA OF AUTOCORRELATION. 9.29E-03 LC FROM AUTOCOMRELATIONE 9.99E+03 VALUES FROM PREDICTOR.AREA OF PSO: 4.90E-03 LC FROM PSO: 1.66E+01 ARFA OF AUTOCORRELATION. 9.29E-03 LC FROM AUTOCOMRELATIONE 9.99E+03 VALUES FROM PREDICTOR.AREA OF PSO: 4.90E-03 LC FROM PSO: 1.66E+01 ARFA OF AUTOCORRELATION. 9.29E-03 LC FROM AUTOCOMRELATIONE 9.40E-03 VALUES FROM PREDICTOR.AREA OF PSO: 4.90E-03 LC FROM PSO: 1.56E+01 ARFA OF AUTOCORRELATION. 9.29E-03 LC FROM AUTOCOMRELATIONE 9.59E+03 VALUES FROM PREDICTOR.AREA OF PSO: 4.90E-03 LC FROM PSO: 1.56E+01 ARFA OF AUTOCORRELATIONE 9.59E+03 VALUES FROM PREDICTOR.AREA OF PSO: 4.90E-03 LC FROM PSO: 1.56E+01 ARFA OF AUTOCORRELATIONE 9.59E+03 VALUES FROM PREDICTOR.AREA OF PSO: 4.90E-03 LC FROM PSO: 1.56E+01 ARFA OF AUTOCORRELATIONE 1.55E-01 LC FROM AUTOCOMRELATIONE 9.59E+03 VALUES FROM PREDICTOR.AREA OF PSO: 4.90E-03 LC FROM PSO: 1.56E+01 ARFA OF AUTOCORRELATIONE 1.55E-01 LC FROM AUTOCOMRELATIONE 9.59E+03 VALUES FROM PREDICTOR.AREA OF PSO: 4.90E-03 LC FROM PSO: 1.56E+01 ARFA OF AUTOCORRELATIONE 1.55E-01 LC FROM AUTOCOMRELATIONE 9.59E+03 VALUES FROM PREDICTOR.AREA OF PSO: 4.90E-03 LC FROM PSO: 1.56E+01 ARFA OF AUTOCORRELATIONE 1.55E+01 ARFA OF AUTOCOMRELATIONE 4.71E-03





USE NORMOL AUTOCORRELATION

THIS IS FILE SIMID IS-DEC-97 SIMULATE DATA WITH SEEG-3333 NUMBER OF POINTS SIMILATED-BOCOO - NUMBIR OF VALLES IN PSD-4006 OUTPUT FROM PARCHEM MODELL IS-DEC-92 PREDICTOR WAS ESTIMATED FROM PSD MODEL, LG= 1.0006.401 SICMAXZ 4.906=.03 SLOPE DF PSD-3.003 SPACTAD= 1.006-01 n= 2.506-02

RL AREA'S OF PSO FARE CORRECTED FOR VALUES ABOVE INTOUIST FHEQUENCY OF -S.COREADD IS 1.12E-08. VALUE'S FROM OMICINAL, AREA OF PSD - 4.50F-03 LE FHOM PSD - 1.00E+01 AREA OF AUTOCORRELATION- 9.29E+00 VALUE'S FROM PREDICTOR, AREA OF PSD = 4.50E-03 LE FROM PSD = 1.56E+01 AREA OF AUTOCORRELATION- 1.55E-01 LE FROM AUTOCORRELATION- 1.55E+02





NUSTBER UF VOLUES IN PSD=4096 USE NORMAL AUTOCURABLATION THIS IS FILE STATE IS DEC-92 STAULATE DATA MITH SEED-3333 NUMBER DF POINTS STAULATED BODOO

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DUTPUT FROM PROCROM HODELI IS-DEC-92

PREDICTOR WAS EXTENDED FRUM PSU MOREL TO TO DEFORT STOMMEZ 4.90K-03 SLOPE DE PSD.3.00 STACTOG 1.00E-01 A= 2.50E-02 ALL AREA'S OF PSU APE COMPECTED FOR VALUES ABOVE MYOUIST FREQUENCY OF 5.00E-00 IS.6.12E-00 VALUES FROM PREDICTOR.AREA OF PSU-4.90E-03 LC FROM PSD.1.00E+01 AREA OF AUTOCOMMELATION=1.27E-01 LC FROM AUTOCOMMELATION=9.39E+00 VALUES FROM PREDICTOR.AREA OF PSU-4.90E-03 LC FROM PSD.1.30E+01 AREA OF AUTOCOMMELATION=1.27E-01 LC FROM AUTOCOMMELATION=1.27E+01 VALUES FROM PREDICTORAREA OF PSU-4.90E-03 LC FROM PSD.1.25E+01 AREA OF AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 AREA OF AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 AREA OF AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 AREA OF AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 AREA OF AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 AREA OF AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 AREA OF AUTOCOMMELATION=1.27E+01 AREA OF AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 LC FROM AUTOCOMMELATION=1.27E+01 AUTOCOMELATION=1.27E+01 AUTOCOMMELATION=1.27E+01 AUTOCOMELATION=1.27E+01 AUTOCOMEL



100 m. Unmodified theoretical autocorrelation function. Twelve predictor coefficients

NUMBER OF VALUES IN PSD\_4095 THIS IS FILE SIMIR IS-DEC-92 SIMULATE DATA WITH SEED.=3333 AUMBER OF POINTS SIMULATED=80000 OUTPUT FROM PROOPEM MODELT IS-OEC-92 USE NDRMRL, RUTUCORRELATION

PREDICTOR MAS ESTIMATED FROM PSD MORT LC= 1,75E+00 STCMARKZ 1,02E-03 SLOPE OF PSD=4.D0 SPECING= 1.00E-01 A= 1.82E-01

PREDICTOR LAS ESTIMATED FROM PSO MOREL LL= 1./AL-AUV SUMMERS 1.VAL-UN SUMMERS 1. COS. 400 15 2.035-08 ALL PREA'S OF PSO ARE CORRECTED FOR VALUES FROME NOUSE FROM FROM FROM PLUCORRELATION 3.555-03 LC FROM PUTCORRELATION 1.755-00 VALUES FROM OREIGNAL, RAREA OF PSO: 1.022-03 LC FROM PSD: 1.756-00 RAREA OF PUTCORRELATION. 3.555-03 LC FROM PUTCORRELATION 1.575-00 VALUES FROM PREDICTOR.AREA OF PSO: 1.022-03 LC FROM PSD: 1.576-00 RAREA OF AUTOCORRELATION. 3.475-03 LC FROM PUTCORRELATION. 1.575-00 VALUES FROM SIMULATED RAREA OF PSO: 1.022-03 LC FROM PSD: 1.576-00 RAREA OF AUTOCORRELATION. 3.475-03 LC FROM PUTCORRELATION. 1.575-00 VALUES FROM SIMULATED RAREA OF PSO: 1.022-03 LC FROM PSD: 1.576-00 RAREA OF AUTOCORRELATION. 3.475-03 LC FROM PUTCORRELATION. 1.576-00 VALUES FROM SIMULATED RAREA OF PSO: 1.022-03 LC FROM PSD: 1.576-00 RAREA OF AUTOCORRELATION. 3.475-03 LC FROM PUTCORRELATION. 1.576-00



Left panel, theoretical PSD input (unmarked), autoregressive predictor PSD (marked by x), and simulated PSD (marked by small square). Right panel, corresponding autocorrelation functions.  $L_c = 1.75$  km, S = -4,  $\sigma^2 = 1.02E-03$ , spacing = 100 m. Unmodified theoretical autocorrelation function. Six predictor coefficients Figure 29.



NUMBER OF VPLUES IN PSD=4096 THIS IS FILE SIMLE 15-DEC-92 STHULATE DATE WITH SEED-3333 NUMBER OF POINTS SIMULATED-80000 DUTPUT FROM PROGPAM MODELL 15-000-92

PREDICTUR LAS ESTIMATED FROM PSU MOUEL LC= 1.756+00 SIGMA#2 1 0°C-U3 JL.75 CF PSO=4.00 SPRCING= 1.000-01 A= 1.826-01 ALL AREA'S OF PSO ARE CORRECTED FOR ARUES PBOVE AROUTISE TREQUENCY OF 5.006-00 IS 2.096-09 VALUES FROM DRICTARL, AREA OF PSO= 1.022-03 LC FROM PSO= 1.726+00 AREA OF AUTOCORRELATION= 3.556-03 LC FROM AUTOCORRELATION= 1.736+00 VALUES FROM PREDICTOR.AREA OF PSO= 1.022-03 LC FROM PSO= 1.756+00 AREA OF AUTOCORRELATION= 3.566-03 LC FROM AUTOCORRELATION= 1.756+00



Figure 30. Autoregressive simulated structure sequence.  $L_c = 1.75$  km, S = -4.  $\sigma^2 = 1.02E-03$ 

USE NORMAL AUTOCORRELATION

NUMBER DF VALUES IN PSD+4096 THIS IS FILE SIMIR IS-DEC-92 SIMULATE DATA WITH SEED-3333 NUMBER OF POINTS SIMULATED=BODOD

54 •

DUTPUT FROM PROCARM MODELT IS-DEC-92 PREDICTOR MAS ESTIMATED FROM PSO MODELTIC: 1,756+00 SICMA\*\*2 1.026-03 SLOPE OF PSO=4.00 SPACTAU: 1.606-01 A= 1.826-01 ALL AREATS OF PSO RAE CORRECTED FOR VALUES ABOVE NYOUIST FREQUENCY OF 5.006+00 IS 2.095-08 VALUES FROM ORIGINAL, AREA OF PSO=1.026-03 IC FROM PSO=1.756+00 AREA OF AUTOCORRELATION= 3.556 03 IC FROM AUTOCORRELATION= 1.736+00 VALUES FROM PREDICTOR AREA OF PSO=1.026-03 IC FROM PSO=1.756+00 AREA OF AUTOCORRELATION= 3.556 03 IC FROM AUTOCORRELATION= 1.756+00





USE NORMAL RULOCORRELATION

NUMBER OF VALUE, 1N PSD=4095 PRENCIOR HAS ESTIMATED FROM PSC MONEL LCH 1.006+01 SIGMAXZ 4.00E-03 SLAPE DF PSD-4.00 SPRCING= 1.00E-01 R= 3.16E-02 MIS IS F.LE SIMIB IS-DEC.92 SIMURATE DATA WITH SEELP-3333 NUMBER OF POINTS SEMULATED GODOO OUTPUT FROM PROCRAM MODELLE IS-OEC-92

AL AREA'S OF PEO PRE CORRECTED FOR VALUES ABOVE MYDYIST FREQUENCY OF 5.000 400 IS 5.127.10 VALUES FROM ORIGINAL, AREA OF PSO- 4.900-03 LC FROM PSO- 1.000401 PREA OF AUTOCORRELATION. 9.800-02 LC FROM AUTOCORRELATION- 1.000401 VALUES FROM PREDICTOR AREA OF PSO- 4.9000-03 LC FROM PSO- 9.900 PREA OF AUTOCORRELATION -3.786-02 LC FROM AUTOCORRELATION- 9.900-00

WALKS FROM STMLAFT) PKER OF PSO- 4.535-01 LC FROM PSD- 1.016+01 RREA OF RUNOCOPRELATION= 9.366-02 LC FROM RUTOCOPRELATION= 1.016+01



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Figure 32. Left panel, theoretical PSD input (unmarked), autoregressive predictor PSD (marked by x), and simulated PSD (marked by small square). Right panel, corresponding autocorrelation functions.  $L_c = 10$  km, S = -4,  $\sigma^2 = 4.9E-03$ , spacing = 100 m. Unmodified theoretical autocorrelation function. Six predictor coefficients



USE NDR., AL AUTOCORRELATION THIS IS FILE SIMID IS-OEC-92 SIMILATE DATA WITH SECO 3333 NUMBER OF POINTS SIMULATED-00000 NUMBER OF VALUES IN PSD-4096 OUTPUT FROM FROM MODELL 15-DEC-92



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8.00€+02

USE NORMAL AUTOCORRELATION

THIS IS FLE STATURE TO THE TRANKING DATA WITH SEFD.=3733 NUMBER DF POINTS SIMULATED.#00000 NUMBER OF VALUES IN PSD.#495 UNTPUT FROM PROCRAM MODELT IS-DEC-92 PREDICTOR MAS FSTIMATED FROM PSU MODELT IS-DEC-92 PREDICTOR MAS FSTIMATED FROM PSU MODELT IS-DEC-92 ALL ARTS IN "55, FROM PSU MODELT IS-DEC-92 MALUES FROM OFTEN FROM PSU: 4.90E-03 LC FROM PSU-1.00E-01 IS S.00E-00 IS S.332E-10 VALUES FROM OFTEN MAS FSTIMATED FROM PSU-4.90E-03 LC FROM PSU-1.00E-01 IS S.32E-10 VALUES FROM OFTEN AT PROCEDED FROM PSU-4.90E-03 LC FROM PSU-1.00E-01 IS S.00E-00 IS S.332E-10 VALUES FROM PREDICTOR, ARE OF PSU: 4.90E-03 LC FROM PSU-1.00E-01 IREE OF AUTOCORRELATIONS 9.90E-02 VALUES FROM PREDICTOR, ARE OF PSU: 4.90E-03 LC FROM PSU- 9.90E,00 AREA OF AUTOCORRELATIONS 9.90E-02 LL FROM AUTOCORRELATIONS 9.90E-00





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autocorrelation functions.  $L_c = 5$  km, S = -5/3, spacing = 200 m. Theoretical autocorrelation function modified at lag = Left panel, theoretical PSD input (unmarked), autoregressive predictor PSD (marked by x). Right panel, corresponding 0. Six predictor coefficients Figure 35.

USE MODIFLED AUTOCORRELATION

THIS IS FILE STATE 15-DEC-92 STAULATE DATA UTH SEED-3333 NAMBER OF POINTS STAULATED-80000 AURBER OF VALUES IN PSD-4096 UNTPUT FROM PROCRAM MODEL | 15-DEC-92

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PALITICTOR WAS EFTIMATED FROM PEUTODEL LE SLODE-DO STORTHAZ 3.02E-DA STORE OF PSD-1.67 STACTORE 1.00E-OT ME 2.30E-D2 1. APEATS OF PSD ARE TORRECTED FOR VALLES PODVE WRONGET FREQUENCE OF SLODE-DO IS 6.10F-GG VALUES FROM PSDICTORA. AREA OF PSD-3.02E-DA LE FROM PSD-5.00E-000 AREA OF ANTOCORRELATION-3.11%-OZ LE FROM MUTCCORRELATIONE. 5.12E-00 VALUES FROM APEDICTORAREA OF PSD-3.05E-OT LE FROM PSD-3.05E-000 AREA OF ANTOCORRELATION-2.11%-OZ LE FROM MUTCCORRELATIONE. 5.12E-00 VALUES FROM APEDICTORAREA OF PSD-3.05E-07 LE FROM PSD-3.05E-000 AREA OF ANTOCORRELATION. 2.21%-COZ LE FROM ANTOCORRELATIONE. 3.45E-00 VALUES FROM STIMULATED AREA OF PSD-3.00E-000 AREA OF ANTOCORRELATION. 2.02E-02 LE FROM ANTOCORRELATIONE. 3.45E-00 VALUES FROM STIMULATED AREA OF PSD-3.00E-000 AREA OF ANTOCORRELATION. 2.02E-02 LE FROM ANTOCORRELATIONE. 3.45E-00 X



Figure 36. Left panel, theoretical PSD input (unmarked), autoregressive predictor PSD (marked by x). Right panel, corresponding autocorrelation functions.  $L_{c} = 5$  km, S = -5/3, spacing = 100 m. Theoretical autocorrelation function modified at lag = 0. Six predictor coefficients

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## Appendix.

### Extensions of AR Methods to Non-Stationary Data and to Two and Three Dimensions

### A1. NON-STATIONARY DATA

The methods employed here easily can be extended to simulate a non-stationary discrete spatial series. If  $L_c$ ,  $\sigma^2$ , or spectral slope are cllowed to vary slowly, sets of  $a_i^k$  coefficients and associated  $\sigma_k^2$  values for each point k can be evaluated, where  $a_i^k$  is the i<sup>th</sup> coefficient at point k with the simulated results starting at k = 1. Y(k) can then be simulated by setting Y(-L) = Y(-L+1) = Y(L+2) = ... = Y(-L+N-1) = 0 (where L is some number, say 100, and N is the number of coefficients). With k = -L+N, -L+N+1, ..., 1, the iterative expression for Y(k) is:

$$Y(k) = \sigma_1 G(k) - \sum_{i=1}^N a_i^1 Y(k-i)$$

and for k > 1, Y(k) is:

$$Y(k) = \sigma_k G(k) - \sum_{i=1}^N a_i^k Y(k-i)$$

#### A2. TWO AND THREE DIMENSIONAL SIMULATIONS

The methods employed in the text can be extended to simulate horizontal and vertical data. Assume we wish to simulate data at altitudes  $k = 1, 2, \cdots$ . Then using either a Fourier transform method or the linear prediction technique, one may form a simulated sequence whose horizontal PSDs are the PSD from the L<sub>c</sub> and slope at each horizontal altitude with  $\sigma$  set to 1. In addition, one must form simulated values at clittudes -L, -L+1, ..., 0 from L<sub>c</sub> and slope (horizontal) for k = 1

and for c set to 1. Let us call the resulting values Z(kj) where k is the altitude and j is a point number (j could represent a point on a horizontal line or, by extension, a point in a twodimensional horizontal sheet). Then the final data having the desired horizontal and vertical PSD's, F(kj), is formed by filtering Z(kj) as follows.

For 
$$k = -L$$
,  $-L+1$ ,  $-L+2$ , ..., 1

$$F(k, j) = \sigma_1 Z(k, j) - \sum_{i=1}^N \alpha_i^{\dagger} Z(k-i, j)$$

where  $\sigma_1$  and  $a_t^1$  are the values found using the Levinson algorithm with  $r_{xx}$  determined from  $\sigma$  and the vertical values of  $L_c$  and slope at altitude =1.

Then for k > 1,

$$F(k, j) = \sigma_k Z(k, j) - \sum_{i=1}^N \alpha_i^k Z(k-i, j)$$

where  $\sigma_k$  and  $a_i^k$  are the values found using the Levinson algorithm with  $r_{xx}$  determined from  $\sigma$  and the vertical values of  $L_c$  and slope at altitude k.

In the above analysis, it should be noted that with careful programming only N+1 altitudes need to be stored at any time during the computations. This can reduce the necessary storage by a factor of 10 or more.