6.9 SPECTRAL CHARACTERISTICS OF SURFACE LAYER TURBULENCE ABOVE SITES OF VARYING SURFACE STRUCTURE DERIVED FROM FLUXNET MONITORING DATA

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1. INTRODUCTION

Standard spectra are often used as a gauge of what eddy-covariance signals should look like. Deviations from that spectral shape are then attributed to shortcomings in instrumentation or measurement conditions. The most common set of standard spectra were derived by Kaimal et al. (1972) from a set of 45 hourly runs of eddy-covariance measurements taken over an extensive stretch of flat Kansas farmland. Here, we investigate whether common spectral shapes are present in long-term eddy-covariance measurements that include many thousands of hours and many different surface types.

Ensemble spectra for fourteen different eddy-covariance tower sites were calculated using high frequency turbulence data provided by ten groups, all part of the FLUXNET community. The canopy heights of the sites used in the analysis span two orders of magnitude and a wide variety of canopy types as well as meteorological conditions.

2. METHODS

Table 1 lists all sites that contributed data to this study along with canopy and measurements heights. For each site a routine was designed to read half-hourly sets of high frequency data from the individual raw data format, in order to produce time series of wind velocities, sonic temperature, carbon dioxide, and water vapor in a common format. Data for the latter two tracers were also converted to mixing ratios.

Subsequent to this initial reading and conversion, all data were treated exactly the same in the post-processing. As a first step all points more than five standard deviations away from a 60 s moving average were removed from the data. This despiking proved necessary because single spikes, e.g. due to data logging errors, produce a white noise spectrum that dominates the signal. After that, the data were rotated three times to yield zero mean lateral and vertical wind speed as well as zero lateral momentum flux. This was done to keep the data treatment consistent with current practice in eddy covariance analysis (Aubinet et al. 2000). After that the data were prepared for the application of a Fourier transform by removing linear trends in all variables and subsequent tapering of the time series using a Hamming window of length 2^k, where k was chosen to make the number of data samples the highest power of 2 below the original number of samples. Within the eddy covariance community there is some debate as to whether detrending should be applied when calculating fluxes. Here, however, we used it to remove variations on scales much greater than the length of the time series because the Fourier transform can only resolve a minimum frequency that corresponds to the length of the time series. Tapering with a smooth function like the Hamming window is common practice in time series analysis (e.g. Press et al. 1992).

Table 1: Canopy and measurement heights

Site	Height (m)	
	Canopy	EC
Vaira Ranch[2a]	0.2	2.5
ARM, Oklahoma[7]	0.3	60
Blodgett Forest[2b]	4	10
Tonzi Ranch[2a]	9	20
Mogostos Forest[8]	12	18
Old Jack Pine[10,3,1]	13	28
Old Black Spruce[3,1]	15	25
Loblolly Pine[9]	15	17
Old Aspen[3,1]	21	39
Walker Branch[2a]	26	36
Park Falls[5]	25	30,122, 396
Solling F1[8]	30	39
Campbell River[1]	33	43
Wind River[6]	60	70

Fourier transforms of all variables were computed and power and cospectra were calculated from these. The high frequency part of these spectra (f > 0.05Hz) was block averaged in 20 logarithmically spaced bins and in total 100 frequency components were stored per half-hour spectrum.

For the main part of the analysis the spectra were normalized by their total variance or covariance and frequencies were divided by wind speed to yield wave number and then normalized by multiplying by measurement height. To calculate ensemble spectra for each site the half-hourly spectra were grouped into daytime and nighttime cases and averaged in 50 logarithmically spaced bins of normalized wavenumbers.

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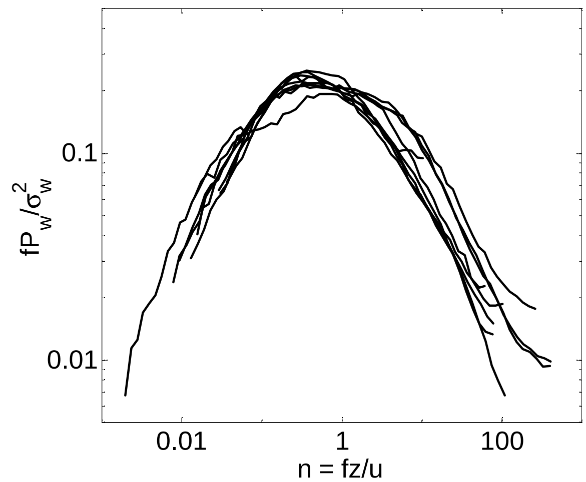

Figure 1: Ensemble power spectra *w* during the day

3. RESULTS AND DISCUSSION

The ensemble power spectra of vertical wind speed *w* during the day collapse onto a single curve for most of the sites when wave numbers are normalized with measurement height (Figure 1). The agreement of spectra from such a range of sites is very encouraging as it shows that it might indeed be possible to characterize turbulence in the surface layer by means of standard spectral shapes.

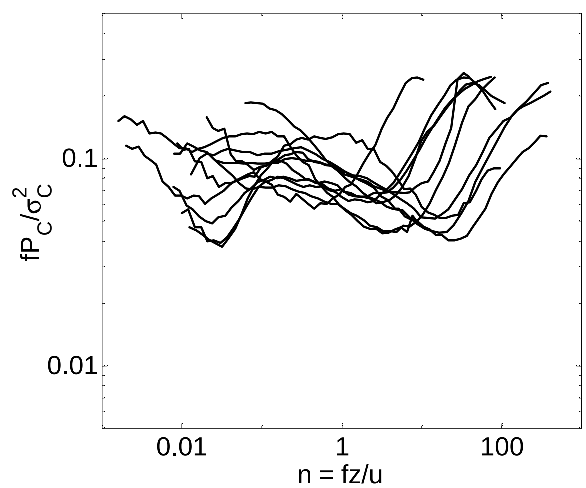

Figure 2: Ensemble power spectra of CO_2 at night

Turbulence, however, does not always dominate the spectra. In the case of the ensemble spectra of carbon dioxide during the night (Figure 2) no single curve is found. Nevertheless, the ensemble spectra show a common pattern as they rise at the high and low frequencies, and have a local maximum in between. This maximum is likely due to the action of turbulence that is expected in this frequency range. At night when turbulence is rather weak, noise at the high frequency end and mesoscale variations at the low frequency end dominate the spectra. The application of improved signal processing techniques such as the use of high-pass filtering instead of linear detrending and proper removal of electronic noise will likely improve these results.

For the cospectra, the same simple averaging of spectra that works rather well for the power spectra does not yield the same smooth results (Figure 3). During the day, the behavior of the ensemble cospectra is generally more erratic than that of the power spectra. This is in part due to the fact that the half-hourly cospectra usually contain positive and negative components even for substantial absolute values of the flux. Hence, other methods for evaluating the ensemble of all cospectra will be discussed in the presentation. Nevertheless, the ensemble cospectra are not influenced by noise or mesoscale variations that dominate the carbon dioxide signal at night and hence it can be inferred that the latter do not contribute to the turbulent flux measurement and that the frequency range covered is sufficient to measure all contributions to the flux.

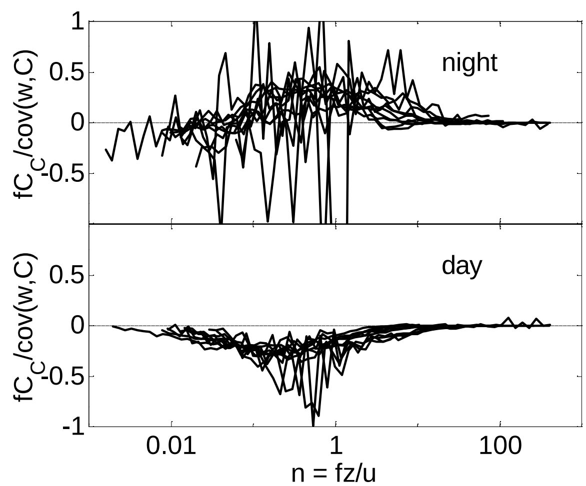

Figure 3: Ensemble cospectra of vertical wind speed and CO_2 during night and day

We conclude that the exercise of processing the vast amount of high frequency data from multiple flux tower sites proved worthwhile indeed as it showed that a) common shapes of surface layer spectra do exist, b) problems with nighttime data exist but do not influence the cospectrum, and c) the frequency range commonly sampled in eddy covariance experiments covers the whole cospectrum for all sites even under difficult conditions and is therefore sufficient to measure all contributions to the turbulent flux.

4. REFERENCES

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