Multiscale analysis of vegetation surface fluxes: from seconds to years

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Abstract

The variability in land surface heat (H), water vapor (LE), and CO2 (or net ecosystem exchange, NEE) fluxes was investigated at scales ranging from fractions of seconds to years using eddy-covariance flux measurements above a pine forest. Because these fluxes significantly vary at all these time scales and because large gaps in the record are unavoidable in such experiments, standard Fourier expansion methods for computing the spectral and cospectral statistical properties were not possible. Instead, orthonormal wavelet transformations (CWT) are proposed and used. The CWT are ideal at resolving process variability with respect to both scale and time and are able to isolate and remove the effects of missing data (or gaps) from spectral and cospectral calculations. Using the CWT spectra, we demonstrated unique aspects in three appropriate ranges of time scales: turbulent time scales (fractions of seconds to minutes), meteorological time scales (hour to weeks), and seasonal to interannual time scales corresponding to climate and vegetation dynamics. We have shown that: (1) existing turbulence theories describe the short time scales well, (2) coupled physiological and transport models (e.g. CANVEG) reproduce the wavelet spectral characteristics of all three land surface fluxes for meteorological time scales, and (3) seasonal dynamics in vegetation physiology and structure inject strong correlations between land surface fluxes and forcing variables at monthly to seasonal time scales. The broad implications of this study center on the possibility of developing low-dimensional models of land surface water, energy, and carbon exchange. If the bulk of the flux variability is dominated by a narrow band or bands of modes, and these modes “resonate” with key state and forcing variables, then low-dimensional models may relate these forcing and state variables to NEE and LE. © 2001 Published by Elsevier Science Ltd.

1. Introduction

Temporal variability in land surface sensible (H) and latent (LE) heat fluxes and net ecosystem exchange (NEE) occur over a wide range of scales ranging from fractions of seconds to decades. These fluxes are interwoven at the most fundamental level, the leaf stomata. Describing the dynamics of H, LE, and NEE requires resolving an extensive high-dimensional spectrum of variability [2]. To date, no one model is able to reproduce the variability in these fluxes across such spectrum of scales. Over seconds, biosphere–atmosphere exchange of water vapor (q), heat (T), and carbon dioxide (C) are governed by complex turbulent eddy motion, rich in spectral properties. At hours to monthly scales, much of the variability is induced by interactions between weather patterns, bulk turbulent flow characteristics, eco-physiological and biochemical characteristics of the canopy, and the hydrologic state of the ecosystem. The latter variable is strongly subject to biological feedbacks by means of stomatal closure and xylem cavitation [40]. At monthly to annual time scales, synoptic weather patterns superimposed on seasonal variations are responsible for changes in ecosystem properties and, consequently, dominate the variability in these land surface fluxes. This multiscale nature of land surface fluxes is now motivating the development of a new generation of canopy–atmosphere models accompanied by long-term measurements [11]. The objective of this study is to explore structural aspects and controls on the temporal spectra of H, LE, and NEE from fractions of seconds to years. A case study is made using measurements of H, LE, and NEE collected over three years at 10 Hz above a 17 year old loblolly pine stand at Duke Forest, near Durham, North Carolina. The Duke Forest site is part of a long-term NEE monitoring initiative

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aimed at representing the ecological behaviour of managed pine plantation in the Southeastern US. About 70% of the total forested area in the Southeastern US (35.6 × 10⁶ Ha) is pines, and 41% of this area is pine plantations younger than 25 years [33]. The site index (= 16 m at 25 years) of the Duke Forest pine plantation also represents the mode of managed pine plantations in the Southeast.

2. Methods of analysis

We propose multiscale methods that can analyze the spectral and cospectral properties of H, LE and NEE. Traditional spectral and cospectral analysis in the Fourier domain is primarily complicated by random gaps in the flux time series measurements and the convolution between these fluxes and the suite of hydrologic and environmental variables at multiple scales. Wavelet transformations can localize the gaps in the flux record and eliminate them from the spectral and cospectral calculations. Additionally, the multiscale interactions between the fluxes and forcing variables are naturally resolved in the standard multiresolution formulation of $\mathcal{C} \mathcal{W} \mathcal{F}$ [13,14,30,31,42,43,47]. Towards this end, all spectral and cospectral properties will be analyzed using $\mathcal{C} \mathcal{W} \mathcal{F}$, as described in the following section.

2.1. Fast wavelet transform (FWT)

The Haar wavelet basis is selected for: (i) its temporal differentiating characteristics, (ii) its locality in the time domain, (iii) its short support which eliminates any edge effects in the transformed series, and (iv) its wide use in atmospheric turbulence research (e.g. see review in [18]), and (v) its computational efficiency. The Haar wavelet coefficients ($d$) and coarse grained signal (or scaling function coefficients) ($S^{(m)}$) can be calculated using the usual multiresolution decomposition on a measurement vector ($f(x_i)$) originally stored in $S^{(0)}$ for $m = 0$ to $M - 1$, where $S^{(0)} = 0$ and $M = \log_2 N$ is the total number of scales. Throughout, $\bar{z}$ is time averaging any variable $z$ over intervals ranging from 20 to 30 min. The decomposition produces $N - 1$ wavelet coefficients defining the Haar $\mathcal{C} \mathcal{W} \mathcal{F}$ of ($f(x_i)$) [26,27].

2.2. Wavelet spectra and cospectra

The $N - 1$ discrete Haar wavelet coefficients satisfy the energy conservation (analogous to Parseval’s identity)

$$\sum_{j=0}^{N-1} f(j)^2 = \sum_{m=1}^{M} \sum_{i=0}^{2^{(m-1)}-1} (d^{(m)}[i])^2,$$

where $m$ is the scale index and $i$ the time (or space) index. The total energy $T_E$ contained in a scale $R_m$ is computed from the sum of the squared wavelet coefficients in Eq. (1) (recall $S(0) = 0$) at a scale index ($m$) using

$$T_E(R_m) = \frac{1}{N} \sum_{i=0}^{2^{(m-1)}-1} (d^{(m)}[i])^2,$$

where $R_m = 2^m dy$ (with $dy = f^{-1}_c$) is the time scale, and $f_c$ is the sampling frequency. Hence, the power spectral density function $P(R_m)$ is computed by dividing $T_E$ in Eq. (2) by the change in frequency $\Delta R_m (= 2^{-m} dy^{-1} \ln(2))$ so that

$$P(R_m) = \frac{\langle (d^{(m)}[i])^2 \rangle dy}{\ln(2)},$$

where $\langle \cdot \rangle$ in Eq. (3) is averaging overall values of the position index $[i]$ at scale index ($m$). Notice that the wavelet power spectrum at $R_m$ is directly proportional to the average of the squared wavelet coefficients at that scale. Because the power at $R_m$ is determined by averaging many squared wavelet coefficients as evidenced in Eq. (3), the wavelet power spectrum is generally smoother than its Fourier counterpart and does not require windowing and tapering. Such averaging in the wavelet domain is statistically stable because of the whitening properties of wavelets (later discussed in greater details). The Haar wavelet cospectrum of two variables (e.g. $w'$ and $c'$, vertical velocity and CO₂ fluctuations, respectively) can be calculated from their respective wavelet coefficient vectors ($d^{(m)}_w$ and $d^{(m)}_c$) at scale $R_m$ using

$$P_{wc}(R_m) = \frac{\langle (d^{(m)}_w[i]) (d^{(m)}_c[i]) \rangle dy}{\ln(2)},$$

where

$$\overline{w'c'} = \frac{1}{N} \sum_{m=1}^{M} \sum_{i=0}^{2^{(m-1)}-1} (d^{(m)}_w[i]) (d^{(m)}_c[i]).$$

While $w'$ and $c'$ are turbulent fluctuations of vertical velocity and CO₂ concentration, with $\overline{w} = \overline{c} = 0$ (see [18,19,21]), the above formulations in Eqs. (4) and (5) are valid for all three scalars.

2.3. Robustness to frequency shifts and gaps in time series

To illustrate the robustness of $\mathcal{C} \mathcal{W} \mathcal{F}$ to time-frequency shifts and to the presence of gaps in the time series, we consider two synthetic experiments. The first experiment considers a frequency change within the time series and contrast its detection by Fourier spectra and wavelet half-plane imaging. The second experiment considers a fractional Brownian motion (fBm) time series, randomly infected by large gaps (typical in long-term flux monitoring), and contrasts the wavelet spectra.
for the original and gap-perturbed synthetic signals. For the first experiment, consider the two signals \( y_1(t) \) and \( y_2(t) \) shown in Fig. 1. These two signals are constructed as follows:

\[
y_1(t) = 0.5 \sin(4t) + 0.5 \sin(32t)
\]

and

\[
y_2(t) = \begin{cases} 
\sin(4t), & t \leq \pi, \\
\sin(32t), & t > \pi.
\end{cases}
\]

Notice in Fig. 1 that the Fourier power spectra for these two signals are nearly identical suggesting that Fourier spectra alone are not well suited to discern these frequency shifts. The squared wavelet amplitudes are shown in the wavelet time–frequency plane in Fig. 1. In contrast to the Fourier power spectrum, the energy is resolved with respect to both scale (or frequency) and temporal extent in the wavelet half-plane. This is an important quality for studying geophysical phenomenon that possess temporal variability in the scale-wise distribution of energy (for example, studies of interdecadal drought variability).

An additional challenge in analyzing long-term flux measurements is the frequent occurrence of random gaps in the measurement record. In fact, many long-term flux monitoring sites within the AmeriFlux and EuroFlux programs have a data recovery rate below 70% and gap events whose duration exceeds 10% of the record size [6]. The occurrence of large gaps precludes the use of traditional Fourier type power spectra. Wavelets, and CWT in particular, offer distinct advantages here. The wavelet coefficients are localized in space, and orthogonal in their relationship to each other, thus limiting the effects of a record gap to the coefficients local to the gap. In computing the global spectra the affected coefficients are simply omitted from the averaging operator. To illustrate, consider a class of non-stationary stochastic processes, known as fractional Brownian motion (fBm) whose statistical properties in the Fourier and wavelet domains are well known (see Appendix A for a brief review). Fig. 2(a) shows an fBm time series with a Hurst exponent \( H_c = 1/3 \). At random, three unevenly spaced, large gaps are injected into this time series (Fig. 2(b)). The gaps collectively represent 30% of the sampling duration for this experiment (a representative value for the Duke Forest AmeriFlux site). The wavelet image of these two time series is also shown in Fig. 2(c) and (d). Notice that the gaps are well localized and can be readily detected in the wavelet half-plane. The wavelet power spectra of these two fBm series are compared in Fig. 3 with excellent agreement between the original and gap-infected time series. In the gap-infected time series, the \( \langle \cdot \rangle \) in the power spectrum definition is applied only to the non-gap-infected coefficients at scale index \( m \).

![Fig. 1. (a) Synthetic time series with and without time–frequency shifts; (b) standard Fourier power spectra for the two series; (c) squared wavelet coefficients in the time–frequency half-plane.](image1)

![Fig. 2. The effects of gaps on wavelet spectral properties: (a) a standard fBm(1/3) time series; (b) a standard fBm(1/3) time series with 30% gaps in the record; (c) and (d) the wavelet coefficients in the time–frequency half-plane.](image2)
2.4. Whitening property of wavelet transformations

An additional desirable feature of wavelets in dealing with time series measurements is their decorrelation property [8,43,47]. Informally speaking, when correlated measurements in the time domain are transformed to wavelet domain, the wavelet coefficients exhibit little or no autocorrelation. Because of this property, wavelets are often called approximate Karhunen-Loève transformations. In terms of a random process \( X(t) \), the Karhunen-Loève transformation is \( \sum Z_i \phi_i(t) \), where \( Z_i \) are uncorrelated random variables and \( \phi_i(t) \) are functions from an orthonormal system, see [43]. To illustrate the decorrelation property of wavelets, we consider two standard test functions: blocks and doppler, for a sample size \( N = 16384 \). The two time series are shown in Fig. 4 (top panels). These two test-signals represent frequency shifts (doppler) and rapid transients (blocks) in time. The lower panels show the autocorrelation function for both time series (dotted) as well as the autocorrelation function for their Haar wavelet coefficients at the finest scale (or level). Notice that the autocorrelation function of the Haar wavelet coefficients decays very rapidly with lag for both signals when compared to the autocorrelation function in the time domain. This rapid decorrelation amongst coefficients is attributed to the so-called whitening property of wavelet transformations. This property is desirable when computing Haar spectral and cospectral functions in Eqs. (3) and (4) because uncorrelated wavelet coefficients provide more stable averages (or statistics) when contrasted to correlated and long-range dependent coefficients. Having discussed the methods of analysis, the experimental setup for measuring \( H \), \( LE \), and \( NEE \) as well as the physiological variables and forcing functions is briefly described.

3. Experiment

3.1. Study site

Hydrometeorological and eco-physiological measurements were conducted at the Blackwood Division of the Duke Forest near Durham, North Carolina (36°2′N, 79°8′W, elevation = 163 m). These measurements, initiated in August of 1997 and continuing to the present date, are part of the (AmeriFlux) long-term flux monitoring initiative. Here, we focus on a long-term period from mid-August 1997 to August 2000. The site is a loblolly pine (Pinus taeda L.) forest, planted in 1983. It extends 300–600 m in the east–west direction and 1000 m in the north–south direction. The mean canopy height \( (h_c) \) was 13.5 (±0.5 m) in 1998. The topographic variations are small (terrain slope changes < 5%) so that the influence of topography on the turbulent transport can be neglected [12].

3.2. Eddy-covariance measurements

The turbulent fluxes (of \( CO_2 \), water vapor, and heat) between the land and the atmosphere were measured by an eddy-covariance system comprised of a \( CO_2/H_2O \) infrared gas analyzer (LICOR-6262, LI-COR, LINCOLN, NE, USA), a triaxial sonic anemometer (CSAT3, Campbell Scientific, Logan, UT, USA), and a krypton hygrometer (KH2O, Campbell Scientific). The anemometer and hygrometer were positioned 15 m above the ground surface and anchored on a horizontal bar extending 1.5 m away from the walkup tower. The hygrometer was used to assess (and support corrections of) the tube attenuation effects in the infrared gas analyzer. The open path hygrometer also provided a reference against which the lag time of the closed path
infrared gas analyzer could be measured, as discussed in [16,17]. Analog signals from these instruments were sampled at 10 Hz using a Campbell Scientific 21X data logger. All the digitized signals were transferred to a portable computer via an optically isolated RS232 interface for future processing. Raw 10 Hz measurements were processed to define 30 min average turbulent fluxes using the procedures described in [16,17,23]. The approximate data recovery rate of the eddy-covariance measurements, shown in Fig. 5, was 65% with downtime due to storms, hurricanes, pump failure, non-optimal wind directions, loss of electrical power, on-site calibration of gas analyzer, and periodic maintenance and factory calibration of instruments. The annual NEE and LE for this stand vary from 580 to 670 g C m⁻² yr⁻¹ and from 520 to 580 mm yr⁻¹ (using a 12 month moving average).

3.3. Other meteorological variables

In addition to the flux measurements, a \( T_e / RH \) probe (HMP35C, Campbell Scientific) was positioned at 15.5 m to measure the mean air temperature (\( T \)) and relative humidity. A Fritchen-type net radiometer and a quantum sensor (Q7 and LI-1908A, respectively, LI-COR) were installed to measure net radiation (\( R_n \)) and PAR, respectively. All meteorological variables were sampled at 1 s and averaged every 30 min using a 21X Campbell Scientific datalogger.

3.4. Hydrologic measurements

Precipitation was measured by a tipping bucket gage (Texas Electronics, Model 525, Dallas, TX) above the canopy every 1 s and integrated every 30 min. The gage has a 476 cm² circular opening catchment area. Soil moisture content \( \theta \) was measured at 24 locations by an array of Campbell Scientific CS 615 soil moisture content vertical rods, each 30 cm in length. The mean of all 24 rods is also shown in Fig. 5. The calibration of these rods is described in [35]. We note that when soil moisture drops below 0.2, cavitation in the xylem-root system is likely to occur thereby reducing the stomatal conductance [29,35]. Such low soil moisture content regimes in the root zone coincide with some of the extended summer droughts recently experienced in the Southeast. In fact, based on our three year record at the site, the time fraction in which the root-zone experienced such low \( \theta \) (or drought) is about 16% as evidenced from Fig. 5.

3.5. \( \text{CO}_2/\text{H}_2\text{O} \) profiles within the canopy

A multi-port system was installed to measure the mean \( \text{CO}_2(\overline{C}) \) and \( \text{H}_2\text{O}(\overline{q}) \) concentration inside the canopy at 10 levels (0.1, 0.5, 1.5, 3.5, 5.5, 7.5, 9.5, 11.5, 13.5 and 15.5 m). Each level was sampled for 1 min (45 s sampling and 15 s purging) at the beginning, the middle, and the end of a 30 min sampling duration. The flow rate within the tube (internal diameter = 1/6") was 0.91 min⁻¹ to dampen all turbulent fluctuations. The modeled concentration profiles within the canopy volume were compared to these measurements every 30 min to assess the accuracy of the modeled source distribution and dispersion calculations. These measurements were also used to investigate the storage flux terms within the canopy volume.

3.6. Leaf-level physiological parameters

The leaf-level physiological parameters were determined from gas exchange measurements by a portable infra-red gas analyzer system for \( \text{CO}_2 \) and \( \text{H}_2\text{O} \) (CIRAS-1, PP-Systems, Herts., U.K.) operated in open flow mode with a 5.5 cm long leaf chamber and an integrated \( \text{CO}_2 \) gas supply system. The chamber was modified with an attached Peltier cooling system to maintain chamber temperature near ambient atmospheric temperature. The data were collected for upper canopy foliage at heights 95% of the total tree height, accessed with a system of towers and mobile, vertically telescoping lifts [5]. These measurements were collected over a broad range of environmental and hydrologic conditions spanning a period of two and a half years (May 1997–October 1999) and were used to define values of all the canopy physiological parameters included in a one-dimensional vegetation-atmosphere coupled photosynthesis–turbulence model (hereafter referred to as CANVEG).
3.7. Plant area density

The vertical distribution of the plant area density (PAI) was measured by gap fraction techniques following the theory presented in [34]. A pair of optical sensors with hemispherical lenses (LAI-2000, LI-COR) was used for canopy light transmittance measurements from which gap fraction and plant area densities were calculated. The measurements were made at 1 m intervals from the top of the canopy to 1 m above the ground to produce the vertical profile in plant area index. PAI measurements were made within two weeks of each of the measurement periods at peak PAI, from the same tower used for measuring the flow statistics, CO₂ concentration profiles and turbulent fluxes.

4. Results and discussion

The H, LE, NEE, θ, and Rₑ time series, shown in Fig. 5, clearly exhibit rich variability at multiple scales. When discussing the spectral properties of land surface fluxes it is helpful to consider three fundamental time scales: fractions of seconds to minutes (turbulent time scales), hours to tens of days (meteorological time scales), and months to years (seasonal time scales). At the very fine time scales, much of the flux variability is induced by turbulent motion whose production is partly governed by the existing mean meteorological conditions. At the hour to days time scale, the interaction between the physiological and biophysical characteristics of the canopy and its micro-climate become the dominant modes of flux variability. Over these fine- and mid-range time scales, the vegetation and its physiological characteristics are assumed, in a first-order analysis, to be static. At longer time scales, seasonal patterns and vegetation dynamics (phenology) share importance with interannual climate variability. The interaction between available energy, hydrologic status, and the vegetation function control the critical modes of temporal variability in heat, water vapor and CO₂ fluxes. Below, we present a framework for representing the processes at their respective time scale.

4.1. Turbulent time scales

At time scales shorter than an hour, the processes governing the land surface fluxes are complex eddy motion. Spectrally, the eddy motion is commonly decomposed into three regimes: production, inertial cascade, and dissipation. The production time scales are the scales in which turbulence extracts energy from the meteorological forcing, with influences by canopy morphology and mean meteorological conditions, particularly the mean longitudinal velocity (U). Scale-wise energy distribution in this range can be well described by hₑ, the friction velocity (uₑ = (uₑw)⁰⁵), and the characteristic scalar concentration fluctuation scale cₑ = wₑ/uₑ [38]. Near the canopy-atmosphere interface (i.e. z/hₑ = 1), the friction velocity (a variable related to the mechanical production of turbulence) is strongly correlated with U (a variable related to the mean meteorological forcing) with U/uₑ ≈ 3.3 [19,38] for near-neutral conditions. In the vicinity of z/hₑ = 1 for rough canopies, the flow is predominantly near-neutral (e.g., >70% of the time for this study). Recent advances in hydrodynamic stability theory suggested that much of the organized motion near the canopy–atmosphere interface, through which the turbulence is produced, is attributed to Kelvin–Helmholtz type instability which scales with hₑ and uₑ. In fact, such theory explained well the spectral peaks in scalar fluxes (e.g. [19]) via a mixing layer analogy. The latter analogy challenged the common paradigm that the structure of turbulence near the canopy-atmosphere interface resembles a rough-wall boundary layer. The role of this organized eddy motion on mass and heat transfer cannot be overemphasized, with more than 90% of the net transport occurring in 10% of the time fraction [21,23]. In the mid-range of turbulent eddy scales we encounter the onset of an inertial cascade, described well by Kolmogorov [9,15,25] type scaling (or K41). This scaling is evident in many scalar spectra and cospectra, with Pₑ proportional to Rₑ⁻⁷/³ as in Fig. 6, with the exception of w/T', for which the power-laws reported near the canopy–atmosphere interface vary from Rₑ⁻⁵/³ to Rₑ⁻⁷/³. The departure from Rₑ⁻⁷/³ has been attributed to the active role of T' in buoyant production or destruction of turbulent kinetic energy, active at these fine scales. At yet smaller scales, the action of molecular viscosity becomes dominant and the turbulent fluctuations are dissipated away as heat. These small scales are in fact finer than the finest scales (10 Hz) measured in this study.

4.2. Meteorological time scales

In this range of time scales, the variations in land surface fluxes are due to the strong and often non-linear interaction between the physiological, radiative, biochemical, and drag properties of the canopy and its microclimate.

To represent such interactions, we developed a one-dimensional multilevel canopy-vegetation model that resolves the key processes in such interaction. The model, now known as CANVEG after [1], is described in [28] but is briefly reviewed below. In its primitive form, the model considers three coupled one-dimensional scalar conservation equations at a level within the canopy volume of thickness dz, in the absence of advective transport:
where $P(z, t | z_0, t_0)$ is the transition probability density function that can be estimated from the velocity statistics within the canopy via a dispersion matrix as discussed in [37]. Higher-order Eulerian closure models for estimating these velocity statistics within the canopy from the drag and foliage distribution are described elsewhere (e.g. [20, 24]) and are used to compute $P(z, t | z_0, t_0)$ or the dispersion matrix. The boundary conditions used in modeling the flow statistics inside the canopy needed to compute $P(z, t | z_0, t_0)$ are presented in Table 1. In short, Lagrangian fluid mechanics principles provide three additional equations to the set of three equations in (6). The Lagrangian frame of reference (or Eq. 7) does not uniquely define such relationships and an equivalent formulation in the Eulerian frame of reference is also possible (e.g. [22]). The later formulation is based on higher-order turbulence closure principles for scalar transport.

To mathematically “close” this problem defined by Eqs. (6) and (7), three additional equations are needed and are derived by assuming the transfer of scalars from the leaf to the atmosphere is governed by Fickian diffusion through the stomatal cavities and within a thin boundary layer at the leaf surface. This approximation leads to:

\[
S_T(z, t) = a(z) \times \frac{(\mathcal{T}_r(z, t) - \mathcal{T}(z, t))}{r_b(z, t)},
\]

\[
S_q(z, t) = a(z) \times \frac{(\mathcal{q}(z, t) - \mathcal{q}(z, t))}{r_b(z, t) + r_c(z, t)},
\]

\[
S_c(z, t) = a(z) \times \frac{(\mathcal{C}(z, t) - \mathcal{C}(z, t))}{r_b(z, t) + r_c(z, t)},
\]

where $r_b$ and $r_c$ are the boundary layer and stomatal resistances, respectively, and $\mathcal{T}_r, \mathcal{q}_r, \mathcal{C}_r$ are the stomatal-cavity temperature, water vapor and carbon dioxide concentrations, respectively. Hence, while the Fickian diffusion approximation in Eq. (8) provided the necessary equations to close the primitive equations, it introduces five additional unknowns: $r_b, r_c, \mathcal{T}_r, \mathcal{q}_r, \mathcal{C}_r$. In the CANVEG approach in [28], these unknowns are determined from the leaf-level energy balance (at each layer within the canopy) and radiation attenuation model of Norman [3], the photosynthesis model of Farquhar [7], the boundary layer resistance ($r_b$) model of [39], and the stomatal conductance ($1/r_c$) model of Collatz [4], given by:

\[
\frac{1}{r_s} = \frac{m}{C_s} + b,
\]

where $m$ and $b$ are species-specific parameters, $A$ is the carbon assimilation rate which depends on $S_c$ and leaf area density $a(z)$ (related to LAI via $LAI = \int_0^L a(z) \, dz$), and $RH(z, t)$ and $C_s$ are the mean leaf relative humidity and CO$_2$ concentration at time $t$ and level $z$. The coupling between the radiative transfer, energy balance, and
Table 1
Key eco-physiological, radiative, and drag properties of the pine forest used in the CANVEG model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leaf area index</td>
<td></td>
<td></td>
</tr>
<tr>
<td>August, 1999</td>
<td>4.52 m²m⁻²</td>
<td>Measured using LAI-2000</td>
</tr>
<tr>
<td>July, 2000</td>
<td>4.31 m²m⁻²</td>
<td>Measured using LAI-2000</td>
</tr>
<tr>
<td>Canopy height (hₖ)</td>
<td>14 m</td>
<td>Measured in 1999</td>
</tr>
<tr>
<td>Characteristic length for calculating rₙ</td>
<td>0.001 m</td>
<td>Measured</td>
</tr>
<tr>
<td>Clumping factor</td>
<td>0.8</td>
<td>Estimated in [28]</td>
</tr>
<tr>
<td>Maximum Rubisco capacity (Vₘₐₓ)</td>
<td>64 µmol m⁻² leaf s⁻¹</td>
<td>Estimated from porometry</td>
</tr>
<tr>
<td>Ball-Berry slope parameter (m)</td>
<td>5.9</td>
<td>Estimated from porometry</td>
</tr>
<tr>
<td>Ball-Berry intercept parameter (b)</td>
<td>0.017</td>
<td>Estimated from porometry</td>
</tr>
<tr>
<td>Maximum quantum efficiency</td>
<td>0.08 mol mol⁻¹</td>
<td>Assumed as in [28]</td>
</tr>
<tr>
<td>Leaf absorbivity for PAR</td>
<td>0.83</td>
<td>Assumed as in [28]</td>
</tr>
<tr>
<td>Drag coefficient</td>
<td>0.2</td>
<td>Estimated from [20]</td>
</tr>
<tr>
<td>At z = 1.15ₖ</td>
<td></td>
<td></td>
</tr>
<tr>
<td>σₚ, /uₜ</td>
<td>2.4</td>
<td>See [28]</td>
</tr>
<tr>
<td>σₚ, /uₜ</td>
<td>1.9</td>
<td>See [28]</td>
</tr>
<tr>
<td>σₚ, /uₜ</td>
<td>1.25</td>
<td>See [28]</td>
</tr>
<tr>
<td>dU/dz</td>
<td>uₚ /k(z - d)</td>
<td>See [28]</td>
</tr>
<tr>
<td>At z = 0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>dσₚ /dz</td>
<td>0</td>
<td>See [28]</td>
</tr>
<tr>
<td>dσₚ /dz</td>
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<td>See [28]</td>
</tr>
<tr>
<td>dσₚ, /dz</td>
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<td>See [28]</td>
</tr>
<tr>
<td>U</td>
<td>0</td>
<td>See [28]</td>
</tr>
</tbody>
</table>

The boundary conditions for longitudinal, lateral, and vertical velocity standard deviations (σₚ, σₚ, σₚ, respectively) used in the second-order closure model are also shown. The mean wind speed U boundary conditions are also presented, with d representing the zero-plane displacement, iteratively calculated by the closure model, and k = 0.4 is von Karman’s constant.

the Farquhar photosynthesis model requires all three scalars to be simultaneously considered in Eqs. (6)–(8) and at each canopy layer. These equations are solved for Fₚ(z, t), Fₛ(z, t), Fₛ(z, t), T (z, t), σₚ(z, t), σₚ(z, t), Sₛ(z, t), Sₚ(z, t), rₛ(z, t), rₛ(z, t), T, q, and c, for specified mean wind speed (U), mean air relative humidity, mean air temperature, mean CO₂ concentration, and PAR in the free space above the canopy every 30 min. The parameters for the Farquhar photosynthesis model, Eq. (9), and the radiation/energy balance are shown in Table 1. The details of implementing these radiative, energy, and eco-physiological schemes in Eqs. (6)–(9) are discussed in [28,29]. While several multilayer radiative-photosynthesis models have been proposed (e.g. [32,44,45]), the present CANVEG model has the added advantage of fully integrating the turbulent transport dynamics and the microclimate to the sources and sinks via Eqs. (6) and (7). Hence, canopy morphology (via a(z)) affects the radiation attenuation, the flow statistics within the canopy, the energy balance, and the scalar source strength at each level in a consistent manner.

To illustrate the CANVEG model performance, a comparison between modeled and measured mean CO₂ concentration inside the canopy volume is shown in Fig. 7. The over-all features of CO₂ buildup during night-time and the well-mixed features during day-time are well reproduced by the CANVEG model. Using a similar approach but with prescribed within-canopy velocity statistics, other studies (e.g. [10]) also report good agreement between measured and modeled CO₂ concentration profiles for a boreal forest. We restate that many of the coupled photosynthesis—radiative transfer schemes (e.g. [32,44,45]) cannot predict the space–time evolution of the mean CO₂ concentration, temperature, and water vapor concentration, but rather require such concentration measurements as input. A comparison between eddy-covariance measured and modeled values of H, LE, and NEE, on a 30 min time step, are shown in Fig. 8 for the same periods as in Fig. 7 with good agreement between measured and modeled fluxes. To assess the spectral recovery of measured H, LE, and NEE by CANVEG, the measured and modeled spectra in Fig. 9 are also compared, with reasonable agreement between these spectra for a wide range of time scales (1 h to 21 days). We restate that in the above calculations, the vegetation was assumed static (i.e. a(z) and all the physiological parameters of the Collatz [4] model, drag properties, and radiative characteristics including foliage clumping are not permitted to vary in time). If the temporal evolution of these canopy physical and physiological properties are known or specified, then the CANVEG model can be used to reproduce the full spectrum of H, LE, and NEE from hours to years.

4.3. Seasonal to annual time scales

While the CANVEG approach can be integrated to seasonal time scales, the temporal dynamics of the
physiological parameters required by such an approach are rarely measured at such temporal resolution [5]. For example, one of the key physiological parameters needed in the Collatz [4] model adopted in our CANVEG is the maximum Rubisco capacity per unit leaf area ($V_{\text{max}}$). For pines, $V_{\text{max}}$ depends on leaf nitrogen concentration, which varies at monthly to annual time scales. Furthermore, the leaf area density profile (as well as LAI) also varies at seasonal time scales thereby altering the radiation attenuation, clumping, and the fraction of sunlit foliage throughout the canopy. Additionally, $a(z)$ dynamics commonly result in phenological and physiological changes with over-wintering foliage having different $m$ and $V_{\text{max}}$ when compared to newly grown foliage. In short, the land surface flux variability at monthly and longer time scales is attributed to changes in forcing and meteorological variables (e.g. $R_n$), hydrologic state (e.g. $\theta$), eco-physiological properties (e.g. $V_{\text{max}}, m$), and ecological properties (e.g. $a(z)$) all convolved at multiple time scales. While such
physiological changes are likely to pose major challenges to modeling water and carbon fluxes at longer time scales, a recent study on six European coniferous forests suggests that long-term water and carbon fluxes can be modeled without using detailed physiological and site specific information [46]. In [46], artificial neural networks were used to select a minimal set of input variables to model LE and NEE without resorting to detailed physiological information. The appeal to a neural network type analysis is to empirically derive highly non-linear relationships between forcing variables and fluxes. Here, rather than producing such empirical non-linear relationships between forcing variables and fluxes, we explore the characteristic time scales which exhibit the largest variability in fluxes and forcing variables as well as the scales which exhibit strongest wavelet spectral correlations.

For this reason, we investigate both measured wavelet spectral and cospectral characteristics of the land surface fluxes with respect to $R_e$ (energy forcing) and soil moisture ($\theta$) (hydrologic state) in Figs. 10 and 11. In Fig. 10, it is clear that at hourly time scales, the three scalar fluxes exhibit larger variability than $R_e$ and $\theta$ (particularly NEE). More important from Fig. 10 is that the seasonal variability for all the variables is at least one order of magnitude more energetic (or important) than the diurnal or daily variability. That is, when annual carbon or water budgets are required, it is the seasonal variability that is critical to resolve. We restate that this pine forest is evergreen and retains foliage (and water flux as well as carbon uptake) year-round. In all the cospectal calculations, the interactions amongst the variables are strongest for seasonal (~200 d) time scales.

For all three land surface fluxes, the seasonal time scales are at least one order of magnitude more im-

Fig. 8. Comparison in the time domain between eddy-covariance measured and CANVEG modeled H, LE, and NEE time series for the two periods: August 1999 (a) and July 2000 (b).

Fig. 9. Wavelet spectral comparison between eddy-covariance measured and CANVEG modeled H, LE, and NEE for the time series shown in Fig. 8.

Fig. 10. Measured Haar wavelet flux spectra for H, LE, NEE, $R_e$, and $\theta$ time series in Fig. 5. For spectral intercomparisons, all the time series are normalized to zero mean and unit variance.
Fig. 11. Measured Haar wavelet flux cospectra for the time series in Fig. 5. For comparisons, the cospectra are normalized by covariances between signals in the Fig. 5 caption.

Fig. 12. Relationship between $R_n$ and LE at multiple time scales: (a) the relationship for the 30 min time scale; (b) variations of LE per unit leaf area at monthly time scales with $R_n$ at the canopy-top; (c) monthly time scales with the solid line representing equilibrium evaporation; (d) monthly variation of LAI with $R_n$.

Fig. 13. Variations of sensible heat H (a) and net ecosystem exchange NEE (b) on $R_n$ for monthly time scales.
5. Conclusions

This study, the first to explore the measured wavelet spectra and cospectra of land surface fluxes from fractions of seconds to three years, demonstrated the following:

- Orthonormal wavelet transformation provides a robust framework for analyzing the spectral and cospectral properties of long-term flux records that exhibit (1) frequency shifts in time, and (2) multiple gaps or missing data.

- The wavelet spectra of the three land surface fluxes (carbon, water, and heat) demonstrated that the largest variability occurs at seasonal time scales. In fact, the energy or activity at seasonal time scales is at least one order of magnitude larger than variability at diurnal (12 h) time scales. As expected, the measured soil moisture spectrum exhibits large activities at seasonal time scales with little activities at sub-daily scales.

- Three broad categories of time scale models must be considered when describing temporal dynamics of land surface fluxes: (1) turbulent time scales (seconds to an hour), (2) meteorological time scales (hours to days), in which physiological properties, radiative transfer, and diurnal boundary layer dynamics interact, and (3) seasonal time scales (weeks to year). The wavelet cospectral comparison suggests that for short turbulent time scales, the Kolmogorov theory describes well observed spectral power-laws. For longer time scales characteristic of turbulent production (100–1000 s), the mixing layer analogy of Raupach [38] reproduces well the observed cospectral peaks in the turbulent flux of water and carbon. The CANVEG model reproduced well the H, LE, and NEE spectra over a broad intermediate range of time scales (hours to days), as long as the vegetation characteristics can be assumed static.

- We showed that on seasonal time scales, the interaction between radiative forcing and land surface fluxes is substantially enhanced when compared to the 30 min time scales consistent with a recent study on six European conifer sites. This enhancement is, in part, attributed to the intricate balance between the flux per unit leaf area, leaf area dynamics, and the seasonal dynamics of $R_n$.

The broad implications of this study center on the possibility of developing low-dimensional models of land surface water, energy, and carbon exchange. If the bulk of the flux variability is dominated by a narrow band or bands of modes, and these modes “resonate” with key state and forcing variables, then low-dimensional models may relate these forcing and state variables to NEE and LE. In fact, current use of remotely sensed data to infer the land surface fluxes in combination with low-dimensional models benefit from such an analysis in two ways: (1) it identifies the time scales at which the remotely sensed observations are likely to “resonate” with the fluxes and hence the time scales at which remotely sensed observations must be resolved, and (2) it identifies the level of predictability that these models can offer given the observed degree of spectral correlation between these observations and the scalar fluxes.

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Appendix A. Properties of fractional Brownian motion

The fBm is a Gaussian, zero mean, continuous, non-stationary process, indexed by the parameter $H_c$ (Hurst exponent, $0 < H_c < 1$) such that

$$B_H(0) = 0, \text{ and } B_H(t + r) - B_H(t) \sim \mathcal{N}(0, \sigma_H^2 | r |^{2H_c}),$$

where

$$\sigma_H^2 = \Gamma(1 - 2H_c) \frac{\cos \pi H_c}{\pi H_c},$$

and $\Gamma(x) = \int_0^\infty t^{-1} e^{-t} dt$ is the Gamma function. From its definition, the sample paths of fBm satisfy the scaling equation $B_H(at) \overset{d}{=} t^{H_c} B_H(t)$, and

$$\langle |B_H(t + r) - B_H(t)|^2 \rangle = C_{\text{fBm}} \cdot |r|^{2H_c},$$

where the $C_{\text{fBm}}$ is

$$\sigma_H^2 \frac{2^{n/2} \Gamma(n + 1/2)}{\Gamma(1/2)}$$

and where $\overset{d}{=} \text{ is equal in distribution}$ [8]. The Fourier transformation of the scaling equation is proportional to $1/|\alpha|^{nH_c+1/2}$ with an average power spectrum proportional to $1/|\alpha|^{2H_c+1}$. 


References


