**Marquette University**

**e-Publications@Marquette**

***Civil, Construction and Environmental Engineering Faculty Research and Publications/College of Engineering***

***This paper is NOT THE PUBLISHED VERSION*.**

Access the published version via the link in the citation below.

*Journal of Geophysical Research Biogeosciences*, Vol. 126, No. 2 (February 2021): e2020JG005865. [DOI](https://doi.org/10.1029/2020JG005865). This article is © American Geophysical Union and permission has been granted for this version to appear in [e-Publications@Marquette](http://epublications.marquette.edu/). American Geophysical Union does not grant permission for this article to be further copied/distributed or hosted elsewhere without the express permission from American Geophysical Union.

Multiscale Legacy Responses of Soil Gas Concentrations to Soil Moisture and Temperature Fluctuations

Anthony J. Parolari

Department of Civil, Construction, and Environmental Engineering, Marquette University, Milwaukee, WI

Joseph Sizemore

Department of Electrical and Computer Engineering, Marquette University, Milwaukee, WI

Gabriel G. Katul

Nicholas School of the Environment, Duke University, Durham, NC

Department of Civil and Environmental Engineering, Duke, Durham, NC

# Abstract

The sensitivity of soil carbon dynamics to climate change is a major uncertainty in carbon cycle models. Of particular interest is the response of soil biogeochemical cycles to variability in hydroclimatic states and the related quantification of soil memory. Toward this goal, the power spectra of soil hydrologic and biogeochemical states were analyzed using measurements of soil temperature, moisture, oxygen, and carbon dioxide at two sites. Power spectra indicated multiscale power law scaling across subhourly to annual timescales. Precipitation fluctuations were most strongly expressed in the soil biogeochemical signals at monthly to annual timescales. Soil moisture and temperature fluctuations were comparable in strength at one site, while temperature was dominant at the other. The effect of soil hydrologic, thermal, and biogeochemical processes on gas concentration variability was evidenced by low spectral entropy relative to the white noise character of precipitation. A full mass balance model was unable to capture high-frequency soil temperature influence, indicating a gap in commonly used model assumptions. A linearized model was shown to capture the main features of the observed and modeled gas concentration spectra and demonstrated how the means and variances of soil moisture and temperature interact to produce the gas concentration spectra. Breakpoints in the spectra corresponded to the mean rate of gas efflux, providing a first-order estimate of the soil biogeochemical integral timescale (~1 min). These methods can be used to identify biogeochemical system dynamics to develop robust, process-based soil biogeochemistry models that capture variability in addition to long-term mean values.

# Plain Language Summary

The ability to describe how climate change impacts soil carbon and nutrient cycles with models is a necessary tool for ecosystem management and sustainability. One difficulty in developing these predictive models is the so-called “legacy effect”—for example, one wet summer may alter the ecosystem for many years afterward. Soil data and models are used here to quantify the relative strength of short- and long-term variability of soil biogeochemical systems and how it responds to rainfall, soil moisture, and soil temperature. We found that variability in soil biogeochemistry is concentrated at longer timescales of several weeks to months and this is because the soil stores water and heat, retaining a “memory” of past rainfall and temperature. Further, this analysis offered a new perspective on the equations used in current models—models driven by soil moisture and temperature are able to capture the legacy in soil biogeochemical data.

# Key Points:

* Soil gases retain variability of precipitation, soil moisture, and temperature at different frequencies
* Soil biogeochemical memory is driven by diffusion at frequencies higher than hydrologic memory
* Linear models driven by soil moisture and temperature capture the main features of the gas concentration power spectrum

# 1. Introduction

Soil biogeochemical processes such as carbon and nutrient cycling and mineral weathering remain a recalcitrant problem in climate science, agriculture, and water resource management. Changes in soil thermal and hydrologic regimes have increased greenhouse gas release through thawing permafrost, enhanced peat decomposition, and increased fertilizer application, representing a positive feedback in the climate-carbon cycle system (Griffis et al., 2017; Heimann & Reichstein, 2008; Ise et al., 2008; McCalley et al., 2014). Yet, the sensitivity of soil carbon and nutrient cycles to climate change continues to pose a formidable challenge to the science of global change and sustainability research (Luo et al., 2016). For example, modeled and data-informed estimates of heterotrophic respiration and soil organic carbon sequestration carry uncertainties as high as 50–100% (Konings et al., 2019; Tian et al., 2015). Improved model representation of soil biogeochemical processes and how they respond to soil and atmospheric conditions remains, to say the least, a “first-order” problem to date.

Soil moisture and temperature variations are the primary physical drivers of soil biogeochemical process rates in the critical zone. Soil moisture and temperature influence rates of root and microbial respiration, decomposition, nutrient and metal cycling, and mineral weathering through physical, chemical, and biological pathways (Cook & Knight, 2003; Duncan et al., 2015; Jarecke et al., 2016; Kumagai & Kume, 2012; Manzoni & Porporato, 2009; Olshansky et al., 2019; Riveros-Iregui et al., 2007; Sierra et al., 2017; Wang et al., 2015; Warrinnier et al., 2020; Zhang et al., 2015). In general, reaction rates increase with soil temperature due to thermodynamic constraints, while the effect of soil moisture is more complex (Moyano et al., 2013). In dry soils, reaction rates increase with soil moisture as microbial osmotic stresses are overcome and soil pore connectivity increases substrate mobility (Manzoni & Katul, 2014). In contrast, as soil moisture increases above field capacity, metabolic process rates begin to decrease as metabolism shifts from aerobic to anaerobic pathways. This shift from aerobic to anaerobic processes results from a decrease in soil diffusivity in saturated soils, which limits resupply of atmospheric oxygen to the soil through diffusion. When oxygen is in limited supply, anaerobic metabolic processes dominate because they are more energetically variable in the absence of oxygen (Burgin et al., 2011). When anaerobic processes dominate, soil CO2 production is reduced, while production of CH4, N2O, and N2 is elevated, along with reduction of redox active metal hydroxides (e.g., Fe, Mn) (Burgin & Groffman, 2012; Jarecke et al., 2016; Liptzin et al., 2011; Warrinnier et al., 2020). Shifts in active soil biogeochemical processes and associated changes in pore water chemistry can occur rapidly during infiltration or recharge events (Austin et al., 2004; Duncan et al., 2015; Jarecke et al., 2016; Olshansky et al., 2019).

These processes are all mediated by the dynamics of complex networks of mineral aggregates, organic matter, microbes, and mycorrhiza. Pools of reaction substrates and mediators have residence times that range from days to decades or more (Bolker et al., 1998). In addition, vertical transport and gradients in substrate availability can induce storage effects that decouple deep processes from surface fluxes (Ryan et al., 2018). This wide range of timescales indicates that below-ground processes can retain a memory, or a legacy, of past soil and atmospheric hydrologic states (Vargas et al., 2011, 2010). Both soil moisture and temperature variability within the rooting zone are characterized by long-range auto-correlations that operate on differing timescales (Katul, Porporato, Daly, et al., 2007; Katul, Porporato, & Oren, 2007; Franzke et al., 2020). Disentangling the signature of such long-range dependence on physical and biochemical drivers of soil biogeochemical processes is a necessary first step for developing parsimonious modeling strategies to address uncertainties in the climate-carbon cycle feedback and soil sustainability.

Long-range dependence in auto-correlation is routinely analyzed using spectral methods. These methods comprise both linear and nonlinear time-series approaches to data analysis and model discovery (Halley & Inchausti, 2004; Kantz & Schreiber, 2004; Priestley, 1981). A first step toward identifying long-range dependence in an environmental process is analysis of the power spectrum. Power spectra derived from data and models can be combined to test model structures and to identify governing processes and error sources (Katul, Porporato, Daly, et al., 2007; MacMynowski & Tziperman, 2010; Hensley et al., 2018). When the process is described by a linear differential equation, this analysis can be carried out analytically (Katul, Porporato, Daly, et al., 2007; MacMynowski & Tziperman, 2010). Other methods, such as wavelet analysis (Torrence & Compo, 1998; Vargas et al., 2010) and various machine learning approaches (e.g., Rasp et al., 2018; Shen, 2018), complement the power spectrum, allowing for time-dependent estimation, and improved prediction; however, at the expense of additional degrees of freedom in the analysis.

To explore long-range dependence in soil biogeochemical systems and its dependence on climate, the spectral properties of soil gas concentration time series are analyzed in relation to precipitation, soil moisture, and temperature fluctuations. Specifically, we ask what modes of variability in precipitation, soil moisture, and soil temperature impact the strength and timescale of variability of physical and biogeochemical processes that control soil gas concentration fluctuations. The question is addressed using a combination of linear dynamical systems models and high frequency concentration data at two sites, one with soil oxygen and the other with soil carbon dioxide measurements.

# 2. Methods

## 2.1. Soil Dynamics in the Time Domain

As a logical starting point, a homogeneous soil defined by an active root-zone depth, , porosity, , and volumetric soil water content, is considered, where is the degree of saturation ( when all soil pores are filled with water). A mass balance of a slightly or sparingly soluble gas such as carbon dioxide or oxygen, , can be expressed in terms of its sources and sinks as

(1)

where is the diffusion flux from the atmosphere into the soil (for oxygen) or conversely (for carbon dioxide), is the respiration flux along with other source-sink terms (negative for oxygen, positive for carbon dioxide), is the gas phase concentration, and is soil temperature. In general, and can be functions of , , and . The total mass is the sum of the gas and liquid phase contributions, which is assumed to be in chemical equilibrium with the gas phase, so that

(2)

where is a variable retardation factor that depends on and , is the Ostwald solubility coefficient, and is the universal gas constant (Davidson et al., 2006; Simunek, Jiri and Suarez, Donald L, 1993).

The gas phase diffusivity depends on and , which when combined with a bulk model for results in

(3)

where is the molecular diffusivity of the gas in free air normalized by a diffusion length scale, and is the atmospheric gas concentration above the soil surface. The soil moisture and temperature adjustment factors in Equation 3 are assumed to be and (Daly et al., 2009; Moyano et al., 2013; Suwa et al., 2004; Turcu et al., 2005). This representation of is lumped or vertically integrated and does not explicitly resolve the contributions of each soil layer as conducted in detailed multilayer models described elsewhere (Daly et al., 2009; Fang & Moncrieff, 1999; Simunek, Jiri and Suarez, Donald L, 1993; Suwa et al., 2004). It is assumed here that for carbon dioxide and oxygen, liquid-phase diffusion is negligible relative to gas-phase diffusion, which is a plausible assumption (Daly et al., 2009; Moldrup et al., 2000).

Lastly, gas-phase production or consumption through respiration and other biogeochemical transformations are represented as a product of a concentration-dependent respiration model, , adjusted by limitations arising from and . That is,

(4)

In general, the respiration function, , can take on a number of forms. Typical forms range from a constant source term to nonlinear Michaelis-Menten dependence on multiple substrates (Davidson et al., 2012; Zhang et al., 2015). As noted earlier, the respiration flux will be positive for carbon dioxide (produced) and negative for oxygen (consumed). The soil moisture and temperature adjustment functions in Equation 4 are assumed to be and (Barron-Gafford et al., 2011; Suwa et al., 2004; Zhang et al., 2015).

Each of the variables (i.e., ) and their functions can be written in the form, , where the overbar denotes the temporal mean and the apostrophe denotes fluctuations around the mean. A linearized form of the model (1) can be obtained by making this substitution and retaining only the first-order terms,

(5)

where a linear respiration function was assumed, is the mean concentration deviation from the atmospheric value, and fluctuations in the retardation factor were assumed negligible.

## 2.2. Soil Dynamics in the Frequency Domain

The ordinary differential equation describing the soil gas mass balance defined in Equations 1–4 can be transformed from the time (or ) domain to the frequency (or) domain by the Fourier transform to yield,

(6)

where the Fourier transform of a function is defined as .

The Fourier transform of the linear model, Equation 5, can be solved analytically to obtain,

(7)

where

(8)

and and are the unmodified diffusion and respiration frequencies of the linear system, respectively. The frequencies are in units of inverse time and the adjustment functions are unitless [−]. The is the integral timescale of the biogeochemical system.

The soil moisture and temperature adjustment functions take on different ranges of values and it is convenient to continue with normalized variables. The Fourier transforms of the variables and the adjustment functions normalized by their standard deviation are equivalent, i.e.,

(see Figure S1). With that substitution,

(9)

where

(10)

and

(11)

The frequencies and are referred to as the soil moisture and temperature gain coefficients, respectively. Note that the coefficients in Equation 9 are crossing, meaning that the soil moisture gain is multiplied by the temperature transform and vice versa.

Equation 9 then leads to the squared Fourier amplitudes defining the power spectrum of as

(12)

Where the power spectrum is .

Equation 12 relates the distribution of soil gas concentration variance across frequencies, , to that of the external fluctuations in environmental parameters, and . To a first order, the gas concentration spectrum, , is a superposition of and that is modulated relative to these spectra by the timescales inherent to soil physical (diffusion) and biogeochemical (dissolution, respiration) processes. These effects are represented by the coefficients , , and , which each contain contributions from the timescales and and the means and standard deviations of the and adjustment functions. Naturally, this simplistic representation can be criticized *ad-infinitum* given the bulk representation and the multiple linearizations adopted. Nonetheless, it does serve as a reference (or a null) model to interpret multiscaled data and provide causal links between environmental variability (e.g., precipitation and temperature) and soil gas concentration fluctuations.

Another advantage of this representation is a clear definition of the biogeochemical system spectral transfer function, which relates the ratio of the concentration spectra (output) to environmental variability (input) (Stoy et al., 2009). The variance-normalized spectral transfer function for input variable, *i*, is defined as . The transfer functions quantify the frequency response of the biogeochemical system for a given input (MacMynowski & Tziperman, 2010; Stoy et al., 2009). Transfer functions for soil moisture, temperature, and precipitation are presented below. Although precipitation is not included in the model here, the spectral characteristics of precipitation are expressed in the soil moisture signal at the observed frequencies (Katul, Porporato, Daly, et al., 2007).

## 2.3. Spectral Entropy

The spectral entropy (SE) quantifies the relative amount of deterministic, process-driven information contained within each time series. The SE here is defined as the Shannon information entropy of the power spectral density function normalized by the variance, . As discussed elsewhere, applying the Shannon information entropy to spectra (instead of probability of the time series of the variable) is acceptable because the normalized spectrum abides by the same probability axioms of information entropy (Wesson et al., 2003). Hence, the discrete probability of variance associated with frequency bin can be defined as,

(13)

and the SE can then computed as,

(14)

where is the number of frequency bins over which the sum is conducted.

The range of SE is confined to and the maximum possible value, , corresponds to white noise. Larger values of SE indicate a more uniform distribution of variability across frequencies and, therefore, a more stochastic (and less deterministic) signal. In the limit of , all frequencies contribute equally to the variance. This state can be labeled as the most ‘disordered’ because there is no dominant timescale explaining the variability in gas concentration fluctuations. On the other hand, smaller values of SE indicate a less uniform distribution of variance across frequencies (or timescales) and thus a more deterministic, process-driven state. In this case, the activity or variability of the process is controlled by few modes with predefined timescales. If those timescales are identified (and linked to and ), then the associated biogeochemical processes operating on such timescales can be delineated and used in any causal explanation.

Because the spectral density functions are of different lengths (between the study sites), the SE of each time series is reported relative to its maximum possible value, i.e., (or relative entropy). In terms of analog to entropy in statistical mechanics (i.e. , where is the Boltzmann constant and is the number of arrangements the microstate can attain in a system) it is worth noting that variability (or energy) at each is analogous to a “micro” state, whereas SE reflects an aggregate or “macro” state of the fluctuations.

Table 1 *Model Constants and Parameters a*

|  |  |  |  |
| --- | --- | --- | --- |
| Oxygen, O2 Carbon dioxide, CO2 |  |  |  |
| Atmospheric concentration, | ppm | 2.095 × 106 | 410 |
| Diffusivity in air, | cm2 s−1 | 0.176 | 0.157 |
| Solubility coefficient, | – | 0.0318 | 0.8317 |
|  |  | Milwaukee, WI | Duke Forest, NC |
| Porosity, | – | 0.50 | 0.55 |
| Root depth, | cm | 10 | 7 |
| Respiration rate, | m d−1 | 0.023 | – |
| Mean respiration flux, | m *μ*mol mol−1 C d−1 | – | 0.42 |
| Soil moisture response, | d−1 | 0.2 | 0.5 |
| Temperature response, | – | 2.7 | 2.7 |

aKatul, Porporato, Daly, et al., 2007; Daly et al. (2009); Zhang et al. (2015).

# 3. Data

Measurements from two field experiments are used to assess the spectral links between precipitation, soil moisture and temperature, and gas concentration. The first experiment was conducted in an urban agricultural soil in Milwaukee, Wisconsin, from April to September, 2019. Volumetric soil water content, soil temperature, and oxygen concentration (Apogee SO110) were measured at 5-min intervals at a depth of 15 cm. Hourly precipitation was obtained from the Milwaukee airport rain gauge located 10 miles southeast of the study location. The second dataset was obtained from the Duke Forest free air carbon dioxide enrichment experiment conducted in a Loblolly pine forest near Durham, North Carolina, 1998–2005. These data included half-hourly measurements of precipitation above the canopy, interception losses, volumetric water content, soil temperature, and soil carbon dioxide (Vaisala GMT 220) concentration at multiple depths. The data used here were measured by soil sensors nearest to the surface, installed between 2 and 11 cm depth (Daly et al., 2008, 2009). The two datasets provide different soil, vegetation, and climate contexts for the analysis. Soil properties and model parameters for each site are provided in Table 1. Time-series data are provided in the supplemental material, Figure S2.

The power spectra of the environmental variables and gas concentrations were approximated with the general expression,

(15)

where is the slope of versus in log-log space and *β* is an integral frequency where the spectrum displays a breakpoint in the slope. The estimated values of and are summarized in Table 2. When is small relative to the frequencies measured, the well-known noise is recovered (Vasseur & Yodzis, 2004). The physical origin of this expression is apparent in the role of in Equation 12 and is derived for reference in Appendix A.

Table 2 *Estimated Parameters for the Theoretical Power Spectra*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Milwaukee |  | Duke Forest |  |
|  | [d] |  | [d] |  |
| Precipitation | 1 | 0, 1 | 1 | 0, 1 |
| Soil moisture | 1 | 1.7, 2.7 | 112, 1 | 0, 1.75, 2.75 |
| Temperature | 0.56 | 1.2, 2.3 | 3.5 | 1.25, 2.75 |
| Concentration | 2.7, 0.09 | 0.9, 1.8, 3.8 | 7.7 | 1.5, 2.25 |

*Note*. (Equation 15): [d] is the integral timescale associated with a breakpoint in the power spectrum slope and is the slope of the spectrum in log-log space. For spectra with multiple breakpoints and slopes, each are listed in order of increasing frequency (decreasing timescale).

# 4. Results and Discussion

The generic spectral properties of the forcing variables (precipitation, soil moisture, and soil temperature) and the soil biogeochemical state variables (oxygen and carbon dioxide concentrations) are first introduced. Next, the behavior of the soil biogeochemical system is demonstrated using the Shannon Entropy as a measure of organization and the linear transfer functions as an indicator of how the soil system processes physical hydro-climatic inputs into bio- geochemical outputs. Finally, the spectral linkage between the forcing and response variables is discussed using the simplified model introduced above.

## 4.1. Empirical Power Spectra

For the Milwaukee site, the power spectrum of precipitation was approximately “white” for subdaily frequencies and was approximately “pink”, decaying according to a power-law , at higher frequencies (Figure 1a). The power spectrum of soil moisture decayed at a rate for low frequencies and for high frequencies, indicating that spectral decay of soil moisture was larger relative to that of precipitation by a factor of 1.7. The power spectrum of temperature decayed at a rate for low frequencies and for high frequencies, demonstrating large damping of high frequency variability expected for the high thermal inertia of soils. The temperature spectrum also showed a strong diurnal signal at 12 and 24 h, as expected.

The power spectrum of soil oxygen retained some modes expressed by the driving variables, but also contrasted their behavior particularly at low frequencies. Similar to temperature, the oxygen spectrum showed peaks at 12- and 24-h frequencies, indicating the diurnal control of temperature on respiration (Riveros- Iregui et al., 2007; Zhang et al., 2015). Soil oxygen exhibited three spectral scaling regimes, with slopes of − 0.9 for low frequencies, − 1.8 for intermediate frequencies, and − 3.8 for high frequencies. For intermediate and high frequencies, the soil oxygen spectrum displayed similar behavior to the soil moisture and temperature spectra. However, it decayed more slowly for low frequencies less than , which corresponds to approximately weekly timescale.

At the Duke Forest site, precipitation and soil moisture showed similar behavior as the Milwaukee site (Figure 1b). The precipitation spectrum decayed at frequencies higher than ~1 day and the soil moisture spectrum was dampened relative to precipitation, decaying according to relative to the precipitation spectrum. Similar to the Milwaukee site, the Duke Forest temperature spectrum was more dampened at high frequencies, decaying at a rate for low frequencies and for high frequencies. The temperature spectrum also showed a strong diurnal signal at 12 and 24 h.

In contrast to oxygen concentration at the Milwaukee site, the Duke Forest carbon dioxide power spectrum was more similar to soil moisture and temperature. The carbon dioxide spectrum exhibited two similar scaling regimes, decaying at a rate for low frequencies and for high frequencies.

The behaviors of the precipitation and soil moisture spectra shown here have been observed and described previously. Decay of the precipitation spectrum at frequencies larger than 1 day reflects serial correlation among intrastorm rainfall pulses, whereas the approximately white noise at lower frequencies reflects the independence of individual storms. Independence of daily rainfall amounts is often assumed in Poisson-dis- tributed precipitation models driving many stochastic ecohydrological models (e.g., Parolari et al., 2014). The soil moisture spectrum decays much more rapidly than precipitation due to storage in the root zone (i.e., the so-called reddening effect), the implications of which to the climate system are reviewed elsewhere (Delworth & Manabe, 1988). The steepening of the soil moisture spectrum relative to the precipitation spectrum by a power of 2, i.e., was well predicted by a bulk soil water balance with evapo-transpiration losses specified as a linear function of soil moisture (Katul, Porporato, Daly, et al., 2007; Nakai et al., 2014; Ghannam et al., 2016). The powers estimated here, 1.7 and 1.75, are similar to this theoretical prediction.

## 4.2. Spectral Entropy

The spectral entropy values calculated from the observed time series are summarized in Table 3. The values are reported relative to a white noise spectrum such that a value of 1 corresponds to a completely random, white noise (or flat) spectrum and a value of 0 corresponds to a completely deterministic spectrum where all of the power is concentrated at a single frequency.

The precipitation series are the most random with a relative spectral entropy of 0.92 for Milwaukee and 0.97 for Duke Forest. Therefore, both precipitation series are nearly white.



Figure 1. Empirical power spectral density normalized by variance, , for precipitation, soil moisture, temperature, and soil gas concentration for (a) oxygen data at Milwaukee, Wisconsin, April–September 2019 and (b) carbon dioxide data at Duke Forest, North Carolina, 1998–2005. The black lines represent the power spectra fit to Equation 15 and the estimated slopes are annotated. The estimated slopes and breakpoints are also tabulated in Table 2.

Table 3 *Spectral Entropy Relative to a White Noise Time-Series with Spectral Resolution m*

|  |  |  |
| --- | --- | --- |
|  | Milwaukee | Duke Forest |
| Precipitation | 0.92 | 0.97 |
| Temperature | 0.33 | 0.18 |
| Soil moisture | 0.27 | 0.35 |
| Concentration | 0.45 | 0.31 |

*Note*. , where spectral entropy is defined as the Shannon Information Entropy of the variance-normalized power spectral density. A value of 1 corresponds to a completely random, white noise spectrum, while a value of 0 corresponds to a completely deterministic spectrum where all power is concentrated at a single frequency

The soil moisture and temperature series are more organized in the spectral domain compared to precipitation. The spectral entropy at Milwaukee was 0.33 for temperature and 0.27 for soil moisture, whereas the values were 0.18 and 0.35 at Duke Forest, respectively. Because these values are closer to 0 than 1, they indicate that the soil physical drivers of respiration are process-dominated, but retain of the stochastic variability in the environmental forcing. This result is consistent with the substantial spectral decay relative to the precipitation spectrum (Figure 1). The smaller spectral entropy for temperature relative to soil moisture at Duke Forest is likely related to either stronger diurnal temperature variations or larger spectrum coefficients at the lowest frequencies.

Finally, the spectral entropy of O2 at Milwaukee was 0.45, whereas that of CO2 at Duke Forest was 0.31. For Milwaukee, this indicates that the O2 series retained more of the stochastic character of the precipitation series relative to temperature and soil moisture. At Duke Forest, the opposite was observed. That is, the CO2 series had a spectral entropy similar to soil moisture and greater than temperature. Again, this result is consistent with the power spectra. The O2 spectrum decayed slowly at low frequencies relative to the other variables, making it the most similar to the white noise spectrum. In contrast, the CO2 spectrum was most similar to the soil moisture spectrum.

The spectra and their spectral entropies are evidence for a physical mechanism that modulates the relation between precipitation, soil moisture, temperature, and respiration fluctuations across multiple scales. In the next section, empirical transfer functions are introduced to quantify the transfer of energy from physical to biogeochemical variables across frequencies.

## 4.3. Empirical Transfer Functions

The soil biogeochemical system filtered fluctuations in the physical drivers at different timescales, as shown by the empirical transfer functions (i.e., ) illustrated in Figure 2. For frequencies where the transfer function exceeds 1, the soil gas concentration exhibits more variability at that frequency than the environmental driver (and vice versa).



Figure 2. Variance-normalized empirical transfer functions for (a) oxygen data at Milwaukee, Wisconsin and (b) carbon dioxide data at Duke Forest, North Carolina with precipitation, soil moisture, and temperature separately specified as the system input, .

At the Milwaukee site, oxygen concentration was more variable than soil moisture and temperature across most scales (Figure 2a). O2 exhibited less variability then precipitation at high frequencies and approximate- ly the same at low frequencies. The soil moisture and temperature transfer functions were of similar order of magnitude. However, soil moisture was strongest at intermediate frequencies between two days and 10 h, while temperature was largest at frequencies greater than 10 h. Therefore, the soil acted as a low-pass filter on precipitation, high-pass filter on temperature, and a band-pass filter on soil moisture fluctuations. The multiscale character of the soil O2 spectrum can be related to how the driving variables control oxygen variability across timescales: soil moisture and temperature contributed similarly at intermediate timescales and temperature dominated at subdaily timescales.

At Duke Forest, carbon dioxide concentration was more variable than temperature across most frequencies and slightly less variable than soil moisture (Figure 2b). Similar to Milwaukee, precipitation variability was damped in the CO2 signal at high frequencies and amplified at low frequencies (<10−2 hr−1). Therefore, the soil acted as a band-pass filter on temperature and a low-pass filter on precipitation. Temperature and precipitation variability were primarily expressed in CO2 variability at this site. Temperature and CO2 con- centration exhibit strong seasonality at this site (see Figure S2). Further, strong relations between through- fall depth and CO2 concentration jumps during rain events were observed and analyzed elsewhere (Daly et al., 2008), supporting the findings here.

## 4.4. Modeled Power Spectra

The soil gas concentration power spectra were determined by numerically solving the full model (Equations 1–4) and with the simplified linear model (Equation 12).

The full model performed well compared to the time-series data for both sites (Figure 3). The O2 concentration at Milwaukee is much more strongly influenced by diurnal temperature fluctuations (Figure 3a) than the CO2 concentration at Duke Forest, which is more strongly impacted by rainfall pulses that arrive every few days (Figure 3c). The most conspicuous discrepancy between the model and data is the large predicted decrease in O2, which occurred during periods of high soil moisture.

The full model also reproduced the gas concentration spectra at both sites. For Milwaukee (Figure 4a), the O2 spectrum estimated from the full model matched that from the data best for low frequencies, (i.e., ~10 hr) In contrast, the full model underpredicted the empirical power spectrum at higher frequencies. Note that the model captured the spectral slope at high frequencies (i.e., ~−4), but overestimated the slope at intermediate frequencies. For Duke Forest (Figure 4b), the full model captured the empirical power spectrum across all but the highest frequencies. At high frequencies, (i.e., ~2 h), the spectral decay was overestimated by the full model. Overestimates of spectral decay at both sites indicates that the full model does not accurately preserve spectral content at high frequencies.

The empirical transfer functions and numerical simulations informed further analysis of the linearized model to provide analytical foresight into how the soil biogeochemical system filters fluctuations in the physical driving variables. Contributions of each driving variable and process to the gas concentration dynamics depends on the soil system coefficients , , and . Estimates of these coefficients from the full model parameters in Table 1 are shown in Table 4. The magnitudes of the coefficients are compared below in a discussion of the primary drivers of gas concentration dynamics at each site.

The coefficients can be interpreted as the integral timescales of the soil hydrologic , thermal , and biogeochemical systems, an index of the soil “memory.” Soil storage of moisture, energy, and chemical constituents effectively acts as a low-pass filter on stochastic environmental drivers. Frequency modulation due to storage is determined by the ratio of the storage capacity to the flux. (Delworth & Manabe, 1988; Katul, Porporato, Daly, et al., 2007). For example, the soil moisture memory timescale was previously derived as , the ratio of soil water holding capacity to the maximum evapo-transpiration rate (Katul, Porporato, Daly, et al., 2007). Similarly, the estimated parameter can be interpreted as a memory of the surface energy balance associated with temperature fluctuations damped by thermal dissipation from the surface. The biogeochemical memory estimated here takes a similar form, i.e., . This expression is the ratio of the soil gas storage capacity to the



Figure 3. Results of the numerically integrated full model: (a)–(b) Milwaukee O2 and (c)–(d) Duke Forest CO2.

mean flux due to diffusion and respiration. Note that the soil gas storage capacity includes the retardation factor which represents equilibrium reactions that control the gas phase concentration. A more soluble gas has a larger storage that takes longer to ‘empty’ via diffusion and, therefore, is expected to amplify more the input signal at low frequencies. It is anticipated that the biogeochemical integral timescale will also depend on soil pH, alkalinity, and other properties (Calabrese et al., 2017).

The integral timescales appear as breakpoints in the slope of the versus *f* graph in log-log space. The model estimated values are 102 h−1 for Milwaukee and 39.5 h−1 for Duke Forest (i.e., ~1 min), respectively (Table 4). These values are larger than the largest frequencies measured at either site and, therefore, are not apparent in the observed or modeled spectra. The hydrologic memory, estimated here for Duke Forest as 112 days, is comparable to (Duke Forest) or smaller than (Milwaukee) the lowest frequencies measured and, therefore, is also not apparent in the data. The most prominent breakpoint identified in the concentration spectrum is that associated with the temperature spectrum, or the soil thermal memory. The thermal memory was estimated as 0.56 days for Milwaukee and 3.5 days for Duke Forest.



Figure 4. Comparison of the empirical (o), full numerical model (+), linear model (−), and temperature-driven model (−−) spectra for (a) the Milwaukee oxygen data and (b) the Duke Forest carbon dioxide data. The spectra are multiplied by to reveal their multiscale character. A linear respiration function was assumed for Milwaukee O2 consumption whereas a constant respiration function was assumed for Duke Forest CO2 production. The frequencies corresponding to the hydrologic , thermal , and biogeochemical memory are marked with arrows. Parameters estimated to model the spectrum are included in Tables 1 and 2.

The coefficients and weight the contributions of the soil moisture and temperature spectra in the gas concentration spectrum. According to Equations 10 and 11, these coefficients characterize the bulk rate of gas movement into or out of the soil, or the difference between the mean diffusion and respiration rates, multiplied by the standard deviations of the adjustment functions.

For the O2 dynamics at Milwaukee, the dominant controls were the soil moisture effect on respiration and the temperature effect on diffusion. These effects were of a similar order of magnitude (Table 4), indicating that a combination of soil moisture and temperature variability is important for predicting the soil gas concentration variability, consistent with the empirical transfer functions. A comparison of the full linear model and an approximation driven by temperature only demonstrates that the temperature spectrum dominates at intermediate frequencies and the soil moisture spectrum dominates at high and low frequencies (Figure 4a). Note, because the coefficients are crossing, it is the magnitude of the soil moisture effect on respiration that emphasizes the temperature spectrum at intermediate frequencies and the temperature effect on diffusion that emphasizes the soil moisture spectrum at high and low frequencies. The linear model structure elucidates how the two variables, and , interact to produce the concentration variance and its spectrum.

Table 4 *Contributions of Diffusion and Respiration to the Linear Model Coefficients Calculated From Model Parameters and Variances of Each Variable (i.e., , , and)*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Milwaukee |  | Duke Forest |  |
|  | Diffusion | Respiration | Diffusion | Respiration |
| Soil moisture gain, | 0.034 | −0.45 | −0.25 | −3.5 |
| Temperature gain, | 0.44 | 0.031 | −2.2 | −0.47 |
| Integral timescale, | 92.1 | 9.9 | 39.5 | n/a |

*Note.* The diffusion and respiration contributions refer to the first and second terms, respectively, in Equations 10 and 11. For example, the soil moisture gain, is composed of diffusion, , and respiration, , components

For Milwaukee, the numerical model and its linear approximations all underpredict the O2 spectrum at frequencies greater than hr−1, which corresponds to approximately 10 h timescale (Figure 4a). The empirical transfer functions (Figure 2a) demonstrate that temperature variability is expressed in the O2 fluctuations at these high frequencies. This inconsistency between the models and data highlights that the temperature adjustment factors of respiration and diffusion, and , respectively, used in the model may not be sensitive enough to retain temperature variability at these frequencies. Evidence exists for diurnal regulators of heterotrophic respiration other than temperature, such as photosynthesis and root exudation of carbohydrates (Detto et al., 2012; Stoy et al., 2007; Tang et al., 2005; Wan & Luo, 2003), which may offer one hypothesis to close this gap.

Similarly, for the CO2 dynamics at Duke Forest, the soil moisture effect on respiration and temperature effect on diffusion were the dominant controls (Table 4). The soil moisture effect on diffusion and the temperature effect on respiration were less important. The linear model including only the temperature spectrum gives a good approximation of the CO2 spectrum (Figure 4b). The model is consistent with the empirical transfer functions (Figure 2b), which show temperature fluctuations are amplified broadly across all frequencies.

The linkages between the environmental variables and concentration spectrum can be further illustrated by constructing a minimal model guided by the relative magnitudes of the coefficients in the linear model. For Duke Forest, and . In addition, note that production of CO2 is independent of the soil CO2 concentration—that is, the reaction is not limited by the reactant concentration. In that case, a constant respiration function, , applies. It follows that the concentration terms in the respiration expression of Equation 5 are dropped and . Under those conditions, Equation 12 can be written as,

(16)

Equation 16 predicts that the CO2 gas concentration spectrum exhibits two regimes following the temperature spectrum. At low frequencies, the CO2 spectrum displays a nearly pink noise regime with for *.* At high frequencies, the spectrum follows a “red” regime with , for . The linear model captures all the essential regimes in the observed CO2 spectrum (Figure 4b). This multiscale feature of the CO2 spectrum is emphasized when the spectrum is multiplied by , yet is obscured by sensor noise at high frequencies.

# 5. Conclusions

The spectrum of soil gas concentrations in relation to hydro-climate variables was studied using empirical and modeling approaches. Power spectra, transfer functions, and spectral entropy were quantified from concurrent time-series of precipitation, soil moisture, temperature, and soil gas concentrations (O2 and CO2) at two locations with contrasting soil, climate, and vegetation types. Mass balance models of varying complexity (full nonlinear and linear) were then applied to the data to identify the mechanisms linking variability in external driving variables to the soil biogeochemical state variables.

The data demonstrated certain similarities and differences between the two sites. At both sites, the mean effects of soil moisture and temperature were important, while soil temperature variability dominated the soil gas concentration variability and was key to modeling the system in the time and frequency domains. At the Milwaukee site, the contributions of soil moisture and temperature variability were of similar magnitude with soil moisture more dominant at intermediate frequencies and temperature more important for high, subdaily frequencies. In contrast, at the Duke Forest site, soil temperature variability was the variable most strongly expressed by the soil biogeochemical system, whereas soil moisture variability was less apparent across all frequencies and precipitation was expressed at the lowest frequencies of multiple weeks. The soil O2 data were more stochastic in character and the soil CO2 data appeared more organized, or process-driven. Therefore, the two systems processed precipitation, soil moisture, and temperature fluctuations differently.

Theoretical expressions were derived for the power spectrum of soil gas concentration that generally reflected the conclusions from the data. In general, the soil gas concentration spectrum is a superposition of the soil moisture and temperature spectra that is damped by the diffusion and respiration processes. The weighting of the two spectra is determined by the relative values of the soil moisture and temperature fluctuations. Milwaukee O2 variability at low frequencies was well predicted by a model driven by temperature and soil moisture, while the full model was unable to capture the high frequency variability due to temperature. This highlighted a potential gap in currently modeling capabilities at these scales. Duke Forest CO2 data were well predicted across all frequencies by temperature fluctuations only. In both cases, the “memory” of the soil biogeochemical system was reasonably approximated by the timescale associated with diffusion, on the order of a few minutes. This indicates that strong damping by the soil biogeochemical system only occurs at very high frequencies. However, damping of soil moisture and temperature due to storage is propagated to the soil gas concentrations, which is associated with timescales greater than several days or weeks. The soil thermal memory of 0.5–3.5 days was the damping timescale most apparent in the soil gas concentrations. Therefore, models that operate at the daily scale and higher may be able to capture most soil gas concentration variability.

# Appendix A: Power Spectrum of Environmental Variables

For reference, a general expression for the power spectrum of an environmental variable is derived here. Consider a variable that varies in time only, is driven by random noise , and decays according to a function . A balance equation for can be written as,

(A2)

For a linear loss function, i.e., , Equation A2 can be solved for the Fourier transform of ,

(A3)

The power spectrum is then obtained as the squared amplitudes of the Fourier spectrum,



(A4)

Equation A4 shows that the power spectrum of the variable is related to the spectrum of the noise as well as the rate of the decay process, . The rate is interpreted as the integral timescale or memory of the decay process. When by the factor Alternatively, when the spectrum of is dampened relative to , i.e., . Therefore, the signatures of the external noise and internal process on the variability of can be distinguished from the shape of the power spectrum.

# Data Availability Statement

Data are available from the Dryad Digital Repository https://doi.org/10.5061/dryad.v41ns1rtv (Parolari, 2020).

# Acknowledgments

A. J. Parolari and J. Sizemore acknowledge support from the Fund for Lake Michigan and the Marquette University Opus College of Engineering Summer Undergraduate Research Fellowship. G. G. Katul acknowledges support from the U.S. National Science Foundation (NSF-AGS-1644382, NSF-IOS-1754893, and NSF-AGS-2028633).

# References

Austin, A. T., Yahdjian, L., Stark, J. M., Belnap, J., Porporato, A., Norton, U., et al. (2004). Water pulses and biogeochemical cycles in arid and semiarid ecosystems. *Oecologia*, *141*(2), 221–235.

Barron-Gafford, G. A., Scott, R. L., Jenerette, G. D., & Huxman, T. E. (2011). The relative controls of temperature, soil moisture, and plant functional group on soil CO2 efflux at diel, seasonal, and annual scales. *Journal of Geophysical Research*, *116*(G1), G01023. https://doi. org/10.1029/2010JG001442

Bolker, B. M., Pacala, S. W., & Parton, W. J., Jr (1998). Linear analysis of soil decomposition: Insights from the century model. *Ecological Applications*, *8*(2), 425–439.

Burgin, A. J., & Groffman, P. M. (2012). Soil O2 controls denitrification rates and N2O yield in a riparian wetland. *Journal of Geophysical Research*, *117*(G1), G01010. https://doi.org/10.1029/2011JG001799

Burgin, A. J., Yang, W. H., Hamilton, S. K., & Silver, W. L. (2011). Beyond carbon and nitrogen: How the microbial energy economy couples elemental cycles in diverse ecosystems. *Frontiers in Ecology and the Environment*, *9*(1), 44–52.

Calabrese, S., Parolari, A. J., & Porporato, A. (2017). Hydrologic transport of dissolved inorganic carbon and its control on chemical weath- ering. *Journal of Geophysical Research: Earth Surface*, *122*(10), 2016–2032. https://doi.org/10.1002/2017JF004346

Cook, F., & Knight, J. (2003). Oxygen transport to plant roots. *Soil Science Society of America Journal*, *67*(1), 20–31.

Daly, E., Oishi, A. C., Porporato, A., & Katul, G. G. (2008). A stochastic model for daily subsurface CO2 concentration and related soil respiration. *Advances in Water Resources*, *31*(7), 987–994.

Daly, E., Palmroth, S., Stoy, P., Siqueira, M., Oishi, A. C., Juang, J.-Y., et al. (2009). The effects of elevated atmospheric CO2 and nitrogen amendments on subsurface CO2 production and concentration dynamics in a maturing pine forest. *Biogeochemistry*, *94*(3), 271–287.

Davidson, E. A., Samanta, S., Caramori, S. S., & Savage, K. (2012). The dual Arrhenius and Michaelis–menten kinetics model for decomposition of soil organic matter at hourly to seasonal time scales. *Global Change Biology*, *18*(1), 371–384.

Davidson, E. A., Savage, K. E., Trumbore, S. E., & Borken, W. (2006). Vertical partitioning of CO2 production within a temperate forest soil. *Global Change Biology*, *12*(6), 944–956.

Delworth, T. L., & Manabe, S. (1988). The influence of potential evaporation on the variabilities of simulated soil wetness and climate. *Journal of Climate*, *1*(5), 523–547.

Detto, M., Molini, A., Katul, G., Stoy, P., Palmroth, S., & Baldocchi, D. (2012). Causality and persistence in ecological systems: A nonpara- metric spectral granger causality approach. *The American Naturalist*, *179*(4), 524–535.

Duncan, J. M., Band, L. E., Groffman, P. M., & Bernhardt, E. S. (2015). Mechanisms driving the seasonality of catchment scale nitrate ex- port: Evidence for riparian ecohydrologic controls. *Water Resources Research*, *51*(6), 3982–3997. https://doi.org/10.1002/2015WR016937

Fang, C., & Moncrieff, J. B. (1999). A model for soil CO2 production and transport 1: Model development. *Agricultural and Forest Meteorology*, *95*(4), 225–236.

Franzke, C. L., Barbosa, S., Blender, R., Fredriksen, H.-B., Laepple, T., & Lambert, F., et al. (2020). The structure of climate variability across scales. *Reviews of Geophysics*, *58*(2), e2019RG000657.

Ghannam, K., Nakai, T., Paschalis, A., Oishi, C. A., Kotani, A., Igarashi, Y., Katul, et al. (2016). Persistence and memory timescales in root- zone soil moisture dynamics. *Water Resources Research*, *52*(2), 1427–1445. https://doi.org/10.1002/2015WR017983

Griffis, T. J., Chen, Z., Baker, J. M., Wood, J. D., Millet, D. B., Lee, X., et al. (2017). Nitrous oxide emissions are enhanced in a warmer and wetter world. *Proceedings of the National Academy of Sciences*, *114*(45), 12081–12085.

Halley, J. M., & Inchausti, P. (2004). The increasing importance of 1/f-noises as models of ecological variability. *Fluctuation and Noise Letters*, *4*(02), R1–R26.

Heimann, M., & Reichstein, M. (2008). Terrestrial ecosystem carbon dynamics and climate feedbacks. *Nature*, *451*(7176), 289–292. Hensley, R. T., Cohen, M. J., & Jawitz, J. W. (2018). Channel filtering generates multifractal solute signals. *Geophysical Research Letters*, *45*(21), 11722–11731. https://doi.org/10.1029/2018GL079864

Ise, T., Dunn, A. L., Wofsy, S. C., & Moorcroft, P. R. (2008). High sensitivity of peat decomposition to climate change through water-table feedback. *Nature Geoscience*, *1*(11), 763–766.

Jarecke, K. M., Loecke, T. D., & Burgin, A. J. (2016). Coupled soil oxygen and greenhouse gas dynamics under variable hydrology. *Soil Biology and Biochemistry*, *95*, 164–172.

Kantz, H., & Schreiber, T. (2004). *Nonlinear time series analysis (Vol. 7)*. Cambridge University Press.

Katul, G. G., Porporato, A., Daly, E., Oishi, A. C., Kim, H.-S., Stoy, P. C., et al. (2007). On the spectrum of soil moisture from hourly to interannual scales. *Water Resources Research*, *43*(5), W05428. https://doi.org/10.1029/2006WR005356

Katul, G. G., Porporato, A., & Oren, R. (2007). Stochastic dynamics of plant-water interactions. *Annual Review of Ecology and Evolution and Systematics*, *38*, 767–791.

Konings, A. G., Bloom, A. A., Liu, J., Parazoo, N. C., Schimel, D. S., & Bowman, K. W. (2019). Global satellite-driven estimates of hetero- trophic respiration. *Biogeosciences*, *16*(11), 2269–2284.

Kumagai, T., & Kume, T. (2012). Influences of diurnal rainfall cycle on CO2 exchange over Bornean tropical rainforests. *Ecological Mod- elling*, *246*, 91–98.

Liptzin, D., Silver, W. L., & Detto, M. (2011). Temporal dynamics in soil oxygen and greenhouse gases in two humid tropical forests. *Eco- systems*, *14*(2), 171–182.

Luo, Y., Ahlström, A., Allison, S. D., Batjes, N. H., Brovkin, V., Carvalhais, N., et al. (2016). Toward more realistic projections of soil carbon dynamics by earth system models. *Global Biogeochemical Cycles*, *30*(1), 40–56.

MacMynowski, D. G., & Tziperman, E. (2010). Testing and improving ENSO models by process using transfer functions. *Geophysical Re- search Letters*, *37*(19), L19701. https://doi.org/10.1029/2010GL044050

Manzoni, S., & Katul, G. (2014). Invariant soil water potential at zero microbial respiration explained by hydrological discontinuity in dry soils. *Geophysical Research Letters*, *41*(20), 7151–7158. https://doi.org/10.1002/2014GL061467

Manzoni, S., & Porporato, A. (2009). Soil carbon and nitrogen mineralization: Theory and models across scales. *Soil Biology and Biochem- istry*, *41*(7), 1355–1379.

McCalley, C. K., Woodcroft, B. J., Hodgkins, S. B., Wehr, R. A., Kim, E.-H., Mondav, R., et al. (2014). Methane dynamics regulated by mi- crobial community response to permafrost thaw. *Nature*, *514*(7523), 478–481.

Moldrup, P., Olesen, T., Schjønning, P., Yamaguchi, T., & Rolston, D. (2000). Predicting the gas diffusion coefficient in undisturbed soil from soil water characteristics. *Soil Science Society of America Journal*, *64*(1), 94–100.

Moyano, F. E., Manzoni, S., & Chenu, C. (2013). Responses of soil heterotrophic respiration to moisture availability: An exploration of processes and models. *Soil Biology and Biochemistry*, *59*, 72–85.

Nakai, T., Katul, G. G., Kotani, A., Igarashi, Y., Ohta, T., Suzuki, M., & Kumagai, T. (2014). Radiative and precipitation controls on root zone soil moisture spectra. *Geophysical Research Letters*, *41*(21), 7546–7554. https://doi.org/10.1002/2014GL061745

Olshansky, Y., Knowles, J. F., Barron-Gafford, G. A., Rasmussen, C., Abramson, N., & Chorover, J. (2019). Soil fluid biogeochemical re- sponse to climatic events. *Journal of Geophysical Research: Biogeosciences*, *124*(9), 2866–2882.

Parolari, A. J. (2020). *Multiscale legacy responses of soil gas concentrations to soil moisture and temperature fluctuations*. Dryad Dataset. Retrieved from https://doi.org/10.5061/dryad.v41ns1rtv.(Dataset

Parolari, A. J., Katul, G. G., & Porporato, A. (2014). An ecohydrological perspective on drought-induced forest mortality. *Journal of Geo- physical Research: Biogeosciences*, *119*(5), 965–981. https://doi.org/10.1002/2013JG002592

Priestley, M. B. (1981). *Spectral analysis and time series: Probability and mathematical statistics (Nos. 04; QA280, P7.)*. Academic Press.

Rasp, S., Pritchard, M. S., & Gentine, P. (2018). Deep learning to represent subgrid processes in climate models. *Proceedings of the National Academy of Sciences*, *115*(39), 9684–9689.

Riveros-Iregui, D. A., Emanuel, R. E., Muth, D. J., McGlynn, B. L., Epstein, H. E., Welsch, D. L., et al. (2007). Diurnal hysteresis be- tween soil CO2 and soil temperature is controlled by soil water content. *Geophysical Research Letters*, *34*(17), L17404. https://doi. org/10.1029/2007GL030938

Ryan, E. M., Ogle, K., Kropp, H., Samuels-Crow, K. E., Carrillo, Y., & Pendall, E. (2018). Modeling soil CO2 production and transport with dynamic source and diffusion terms: Testing the steady-state assumption using detect v1. 0. *Geoscientific Model Development*, *11*(5), 1909–1928.

Shen, C. (2018). A transdisciplinary review of deep learning research and its relevance for water resources scientists. *Water Resources Research*, *54*(11), 8558–8593. https://doi.org/10.1029/2018WR022643

Sierra, C., Malghani, S., & Loescher, H. W. (2017). Interactions among temperature, moisture, and oxygen concentrations in controlling decomposition rates in a boreal forest soil. *Biogeosciences*, *14*(3), 703–710.

Simunek, J., & Suarez, D. L. (1993). Modeling of carbon dioxide transport and production in soil: 1. Model development. *Water Resources Research*, *29*(2), 487–497. https://doi.org/10.1029/92WR02225

Stoy, P. C., Palmroth, S., Oishi, A. C., Siqueira, M. B., Juang, J.-Y., Novick, K. A., et al. (2007). Are ecosystem carbon inputs and outputs coupled at short time scales? a case study from adjacent pine and hardwood forests using impulse–response analysis. *Plant, Cell and Environment*, *30*(6), 700–710.

Stoy, P. C., Richardson, A. D., Baldocchi, D. D., Katul, G. G., Stanovick, J., Mahecha, M. D., et al. (2009). Biosphere-atmosphere exchange of CO2 in relation to climate: A cross-biome analysis across multiple time scales. *Biogeosciences*, *6*(10), 2297–2312.

Suwa, M., Katul, G. G., Oren, R., Andrews, J., Pippen, J., Mace, A., & Schlesinger, W. H. (2004). Impact of elevated atmospheric CO2 on forest floor respiration in a temperate pine forest. *Global Biogeochemical Cycles*, *18*(2), GB2013. https://doi.org/10.1029/2003GB002182

Tang, J., Baldocchi, D. D., & Xu, L. (2005). Tree photosynthesis modulates soil respiration on a diurnal time scale. *Global Change Biology*, *11*(8), 1298–1304.

Tian, H., Lu, C., Yang, J., Banger, K., Huntzinger, D. N., Schwalm, C. R., et al. (2015). Global patterns and controls of soil organic carbon dynamics as simulated by multiple terrestrial biosphere models: Current status and future directions. *Global Biogeochemical Cycles*, *29*(6), 775–792.

Torrence, C., & Compo, G. P. (1998). A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society*, *79*(1), 61–78.

Turcu, V. E., Jones, S. B., & Or, D. (2005). Continuous soil carbon dioxide and oxygen measurements and estimation of gradient-based gaseous flux. *Vadose Zone Journal*, *4*(4), 1161–1169.

Vargas, R., Carbone, M. S., Reichstein, M., & Baldocchi, D. D. (2011). Frontiers and challenges in soil respiration research: From measure- ments to model-data integration. *Biogeochemistry*, *102*(1–3), 1–13.

Vargas, R., Detto, M., Baldocchi, D. D., & Allen, M. F. (2010). Multiscale analysis of temporal variability of soil co2 production as influenced by weather and vegetation. *Global Change Biology*, *16*(5), 1589–1605.

Vasseur, D. A., & Yodzis, P. (2004). The color of environmental noise. *Ecology*, *85*(4), 1146–1152.

Wang, L., Manzoni, S., Ravi, S., Riveros-Iregui, D., & Caylor, K. (2015). Dynamic interactions of ecohydrological and biogeochemical pro- cesses in water-limited systems. *Ecosphere*, *6*(8), 1–27.

Warrinnier, R., Bossuyt, S., Resseguier, C., Cambier, P., Houot, S., Gustafsson, J. P., et al. (2020). *Anaerobic respiration in the unsaturated zone of agricultural soil mobilises phosphorus and manganese*. Environmental Science & Technology.

Wan, S., & Luo, Y. (2003). Substrate regulation of soil respiration in a tallgrass prairie: Results of a clipping and shading experiment. *Global Biogeochemical Cycles*, *17*(2), 1054. https://doi.org/10.1029/2002GB001971

Wesson, K. H., Katul, G. G., & Siqueira, M. (2003). Quantifying organization of atmospheric turbulent eddy motion using nonlinear time series analysis. *Boundary-Layer Meteorology*, *106*(3), 507–525.

Zhang, Q., Katul, G. G., Oren, R., Daly, E., Manzoni, S., & Yang, D. (2015). The hysteresis response of soil CO2 concentration and soil res- piration to soil temperature. *Journal of Geophysical Research: Biogeosciences*, *120*(8), 1605–1618. https://doi.org/10.1002/2015JG003047