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ORIGINAL PAPER

Scale-Specific Controller of Carbon and Water Exchanges Over Wheat Field Identified by Ensemble Empirical Mode Decomposition

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Abstract

The exchange of carbon and water in the ecosystem is influenced not only by weather and climatic perturbations but also by vegetation dynamics. The relationship between carbon and water exchange and environment in agro-ecosystem across different temporal scales is not very often been quantified. Spectral analysis of eddy covariance measurements can identify the interactions between environmental and biological factors at multi-temporal scales. Here, we used a new method, ensemble empirical mode decomposition (EEMD), to study the temporal covariance between ecosystem exchange of carbon dioxide (NEE), latent heat flux (LE) and environmental factors in a winter wheat cropping system located at the North China Plain. The results showed that the NEE, LE and environmental factors can be decomposed into 12 significant quasi-period oscillations on various time-scales i.e. hourly, diurnal, weekly and seasonal timescales. Variance of NEE in diurnal, hourly, seasonal, weekly scale was 58.9, 29.6, 4.7, 0.6%, respectively. Variance of LE in diurnal, hourly, seasonal, weekly scale was 55.2, 15.5, 5.1, 1.8%, respectively. The largest of variance contribution is at diurnal time-scale from net radiation (R_n), wind speed (μ) and vapor pressure deficit (VPD) due to daily rhythms in solar radiation. The soil water content varied significantly at a relatively longer time-scale i.e. weekly and seasonal scale. Large variance contribution of ambient temperature (T) (63.4%) and VPD (33.6%) is in trend term due to the significant increasing seasonal trend from winter to summer. The correlation analysis indicated that NEE and LE was correlated highly with net radiation (R_n) at all time-scale, as well as with VPD, ambient temperature (T), and wind speed (μ) in diurnal scale and with soil water in seasonal time-scales. This implied that solar radiation contributed the main variation of carbon and water in short time-scale, i.e. hourly and diurnal. Soil water variation strongly correlated with the seasonal variation of NEE and LE. Furthermore, seasonal signals of NEE and LE synchronized with LAI, which indicated that carbon dioxide and water flux are also regulated by LAI in seasonal time-scale. The quantification of the variation explained by carbon and water fluxes and environmental factors across different temporal scales using EEMD improved the understanding of carbon and water process in a cropping system.

Keywords Multi-scale · NEE · LE · Environmental factor · Ensemble empirical mode decomposition

Introduction

The exchange of carbon and water between vegetation and atmosphere is influenced by many environmental variables such as temperature, sunlight and wind with different magnitude at diurnal, monthly, seasonal, and inter-annual scales (Baldocchi et al. 2001; Katul et al. 2001; Katul and Parlange 1995). Examining the variation of environmental variables and how they drive the exchange of water and carbon between vegetation and atmosphere may provide insights not only for understanding of the role of climate in the terrestrial carbon and water cycle but also for the improvement of land-surface model prediction (Dietze et al. 2011; Stoy et al. 2009; Wang et al. 2011).

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The relationship between ecosystem carbon and water exchange and environmental factors in different temporal scales have been identified by spectral analysis methods (Stoy et al. 2005; Vargas et al. 2010, 2011). These studies revealed that environmental controllers of ecosystem carbon and water exchange varied across temporal scales as well as biome types (Stoy et al. 2009). The carbon and water flux in ecosystems demonstrated a unique aspect in three appropriate ranges of time scales: turbulent time scale, meteorological time scales and seasonal to inter-annual time scales (Katul et al. 2001; Katul and Parlange 1995; Katul et al. 2007). At the sub-hourly and sub-daily scale, variations of ecosystem carbon and water exchange were largely controlled by the responses of photosynthesis and stomata conductance due to temporal variation in solar radiation and vapor pressure (Baldocchi et al. 2001). At meteorological scales, synoptic weather events such as high and low pressure drive the weekly or seasonal variation of ecosystem fluxes. At annual or inter-annual scale, ecosystem carbon and water was regulated by long circulation activities such as ENSO (El Nino-Southern Oscillation) and monsoon (Hong et al. 2010). Previous studies of multi-temporal scale put major focuses on natural vegetation but less on crops in an agro-ecosystem. The agriculture ecosystem is intervened by human activities such as irrigation, fertilization and farming managements (i.e. weeding and pest-control). Understanding the temporal variability of the meteorological factors and their impacts on agriculture carbon and water exchange is a challenge when considering these human disturbances.

Despite the importance of temporal variability in carbon and water exchange, it is still unclear on how physical, biotic factors and management influence carbon and water in farming system across different temporal scales, especially because of the lack of quantitative studies on this topic. Therefore, in this study, we use a spectral analysis method (EEMD, ensemble empirical mode decomposition) to examine the relationship between carbon and water exchange and their environmental and biotic factors at multi-temporal scales in winter wheat at the North China Plain. We try to address following scientific questions: (1) which temporal scales are the most dominant for variation contribution in carbon and water exchange for winter wheat in the North China Plain? Is the feature of spectrum of carbon and water fluxes in agriculture ecosystem similar to other types of nature vegetation? (2) Which biophysical and biotic factors control winter wheat carbon and water exchange at which specific temporal scales? The carbon and water exchange in agriculture ecosystem is an important part of the terrestrial ecosystem carbon and water cycle. Understanding the mechanisms of carbon and water exchange in farmland is useful for improving carbon and water management.

Previous studies have used Fourier Transform (Baldocchi et al. 2001), Wavelet Transform (Katul et al. 2007; Stoy et al. 2007) to examine the periodic features of carbon and water fluxes in nature vegetation. For example, Baldocchi et al. (2001) applied Fourier transform to identify the characteristics of the power spectra of flux of carbon dioxide, water vapor and sensible heat and meteorological variables in a broad-leaved deciduous forest. However, Fourier transform may be only appropriate for the stationary signals which the frequency content does not change with time. In recent years, the Wavelet transform was more often applied to identify temporal multi-scale characteristics of mass and energy flux in soil plant atmosphere continuum (Katul et al. 2001; Katul and Parlange 1995; Katul et al. 2007; Qin et al. 2008; Stoy et al. 2005; Vargas et al. 2010). Compared with the Fourier transform, Wavelet transform can provide temporal/spatial resolution for non-stationary signals with the adjustable frequency dependent window functions called mother wavelets. However, the underling basis of Fourier transform and wavelet transform is not adaptive so sometimes misleads us to interpret intermittent and non-stationary data incorrectly (Hong et al. 2010). As some researchers pointed out that successful application in wavelet transforms for frequency-time information in several cases is not sufficient in resolving the intra-wave frequency modulation (Huang et al. 1998). To overcome the shortage, empirical mode decomposition (EMD) (Huang et al. 1998) has been developed to analyze the non-stationary or non-linear signals like the flux data measured by the eddy covariance observation systems. On the basis of the EMD, to avoid the effect of the possible intermittent noise in the original data (Wu and Huang 2009) added a white noise series to the data series to provide relatively uniform high frequency extreme distribution to facilitate EMD, which was called the EEMD. Based on advantages of intuitive, direct and adaptive properties, EMD and EEMD were broadly applied in analysis of geophysical (Wang et al. 2012), meteorological (Qian et al. 2009) and tower data (Barnhart et al. 2012; Hong et al. 2010). Thus, in this study EEMD was used to assess interactions of multiple variables across multi-temporal scales in a farmland. Consequently in this study, we used EEMD to explore the drivers of carbon and water fluxes at multiple temporal scales using flux observations from a flux towers on winter wheat in the North China Plain.

Materials and Methods

The Study Site and Data

Field experiments have been conducted to monitor the energy and water cycles at Yucheng comprehensive experimental station (36°57′N, 116°36′E, and 23.4 m elevation) in the North China Plain. It is located at Shandong province in the middle and lower reaches of the Yellow River alluvial plain and characterized by continental monsoon climate. Long-term meteorological records indicate a mean annual air of 13.1 °C, mean annual precipitation sum of 528 mm and mean annual solar radiation of 5525 MJ m^{-2}, respectively. The dominant soil type is silty loam with an average density of 1.28 g cm^{-3}. Organic matter content of soil is about 1.12% and the pH is 7.9–8.0. The agriculture managements during the observation in this study are showed in the Table 1.

The eddy covariance observation system and microclimate gradient measurement were placed in the center of farmland. The eddy covariance system was used to measure the concentration of CO_2, sensible and latent heat fluxes with the help of a fast response infrared gas analyzer (LI7500, LI-COR Inc.) and a three dimension sonic anemometer (CSAT3, Campbell Scientific Inc.). Data were recorded with a data-logger (CR23X CSI) and the sampling frequency was 20 Hz for all channel and the average values were calculated and recorded every 30 min. Microclimate gradient measurement system consisted of anemometers (mode AR-100, Vector Instrument, UK) and psychrometers (model HMP-45C, Vaisala, Finland) at height of 2.2 and 3.4 m average. Soil temperature transducers were placed at the depths of soil surface, 10 and 30 cm. Soil moisture sensors were installed at 10 cm and 30 cm depths and soil moisture was monitored with time domain reflectometry (TDR). Solar radiation, net radiation, air pressure and precipitation were measured at an interval of 30 min. All sensors used in the experiment were calibrated strictly. The leaf area of winter wheat was measured weekly during the growing season. More details about the data will be found at Li et al. (2006). The missing data because of the malfunction of instruments or power failure were filled using the linear interpolation when the gaps are less than 2 h and using mean diurnal variation method when the gaps are longer than 2 h. The data including flux of CO_2 (NEE), latent energy (LE), and sensible energy (H) and meteorological variables [air temperature (T), net irradiation (R_n), wind speed (μ), vapor pressure deficit (VPD) and soil moisture (SWS)] are shown in Fig. 1.

EMD and EEMD

The EMD is an adaptive and efficient method to decompose nonlinear and non-stationary data into several components of intrinsic mode function (IMF) using a sifting process. The EMD is base the following three assumptions: (1) the data have at least one maximum and one minimum. (2) The characteristic time scale is defined by the time lapse between the local maximum and minimum. (3) If the data were totally devoid of maxima and minima but included only inflection points, then they can be differentiated once or more times to reveal these local maximum and minimum. IMF must first satisfy that the number of extrema and the number of zero crossings must be equal or differ at most by one. The second is that at any point the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero. IMF represents the oscillation mode imbedded in the data and the modulation of both amplitude and frequency is permitted (Hong et al. 2010; Huang et al. 1998; Wang et al. 2012). Each IMF indicates the specific temporal scale information which imbedded in the original data. The sifting process is used to decompose the data into IMF, which is described as follow:

1. Identify the local maxima and minima of the original data x(t), then all local maxima are connected by a cubic spline from the upper envelope, and minima are connected to form the lower envelop. There mean is designated as m_1, and the difference between x(t) and m_1 as the first component h_1:

$$h_1 = x(t) - m_1. \tag{1}$$

2. However, if h_1 does not satisfy the definition of an IMF, then the process is repeated.

$$h_{11} = h_1 - m_{11}, \tag{2}$$

m_{11} is the mean envelop of h_1.

Repeat this step for k times, until h_{1k} is an IMF.

$$h_{1k} = h_{1(k-1)} - m_{1k}. \tag{3}$$

Then, the first IMF, $c_1 = h_{1k}$ when

$$D_k = \frac{\sum_{t=0}^{T} \left|h_{1(k-1)}(t) - h_{1k}(t)\right|^2}{\sum_{t=0}^{T} |h_{1(k-1)}(t)|^2}.$$

Here, D_k is a stoppage criterion and smaller than a predetermined value such as 0.2.

3. Once the first IMF is removed from the original data, x(t)

$$r_1 = x(t) - c_1. \tag{4}$$

Because r_1 still contains information of longer period components, it is treated as the new data and subject the same sifting process as above. If c_1 or r_1 is smaller than a

Table 1 Agronomic management and mean meteorological variables during the wheat season

Crop	Variety	Sowing date	Harvest date	Irrigation (mm)	Precipitation (mm)	Mean temperature (°C)
Wheat	Keshu 13	2004/10/18	2005/6/10	225.0	101.0	7.1

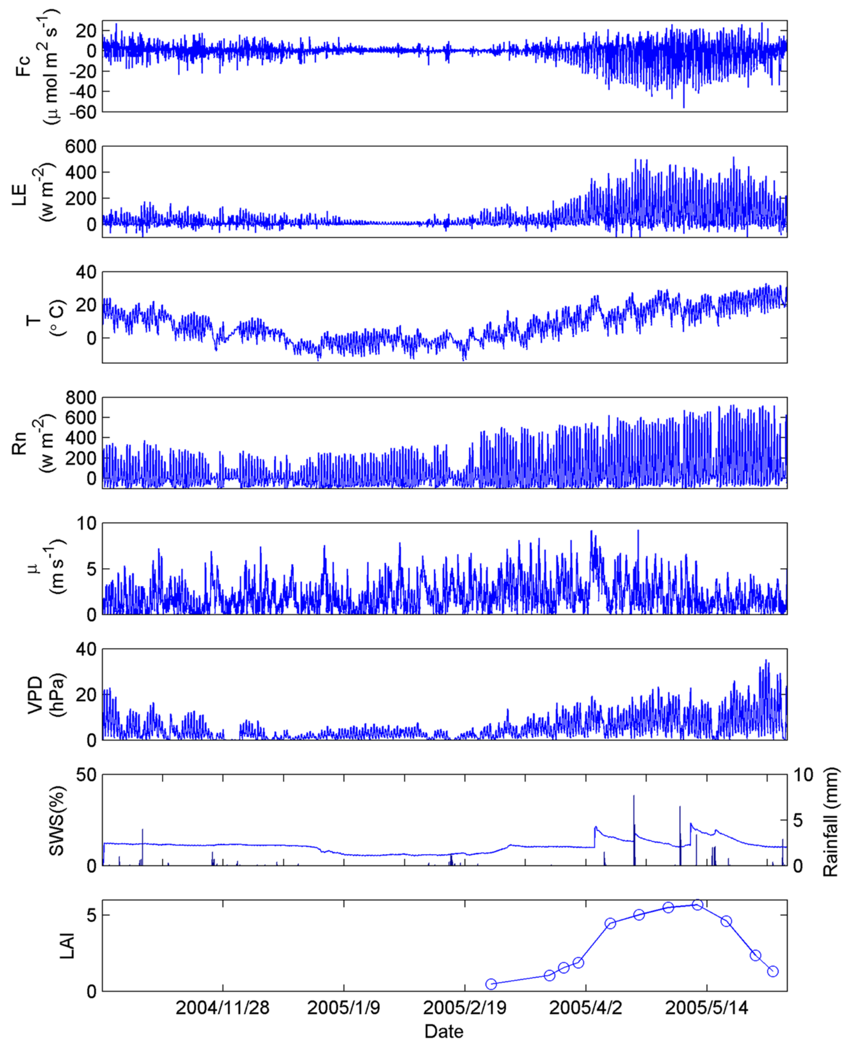

Fig. 1 Time-series data for fluxes (*NEE* exchange of carbon dioxide, *LE* latent heat, *H* sensible heat) and environmental variables (*T* ambient temperature, R_n net radiation, μ wind speed, *VPD* vapor pressure deficit, *SWS* soil water content, rain, LAI), the same as following

predetermined value, or becomes a monotone function, the sifting process is stopped. Thus,

$$r_1 = x(t) - c_1,\ r_2 = x(t) - c_c, \dots r_n = r_{n-1} - c_n. \tag{5}$$

So,

$$x(t) = \sum_{i=1}^{n} c_i + r_n. \tag{6}$$

Thus a series of IMFs can be obtained.

The most significant drawback of EMD is mode mixing, which implies a single IMF consisting of signals of obvious disparate scales or a signal of the same scale appearing in different IMF component. To overcome the problem, Wu and Huang (2009) proposed a new noise assisted analysis method called EEMD. The algorithm of EEMD is described as follow:

1. Add a white noise series to the original signal and decompose the signal with added white noise into IMFs using EMD.
2. Repeat the step 1 but with different white noise series each time and obtain the corresponding IMF components of the decompositions.
3. Adopt the means ensemble corresponding to the IMFs and residue of compositions as the final result.

More detail of EMD and EEMD can be found in (Huang et al. 1998) and (Wu and Huang 2009). The MATLAB code of EMD/EEMD and a simple tutorial will be found at the website (http://rcada.ncu.edu.tw/research1.htm).

After the decomposition, the significance of IMF white noise is tested according to the method proposed in Wu and Huang (2004). The variance of each IMF and residual were

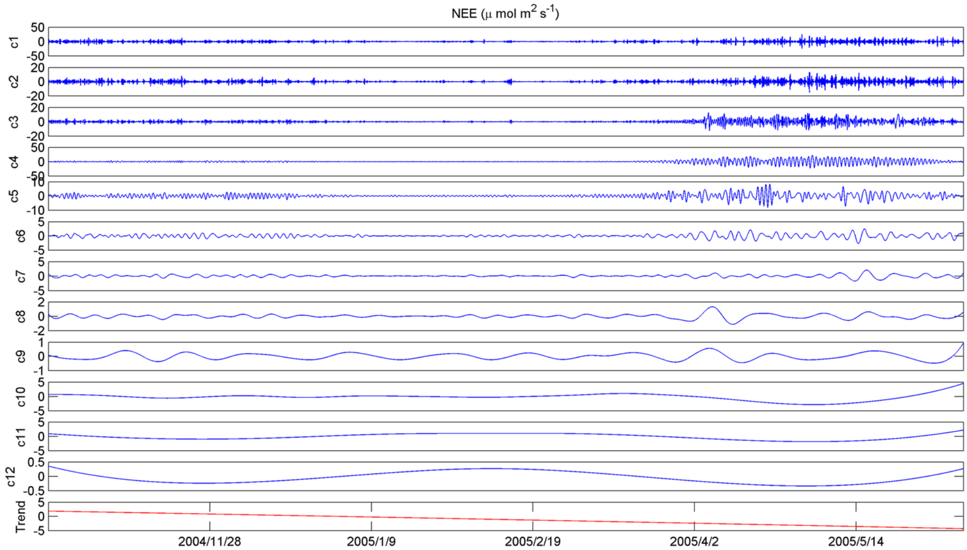

Fig. 2 The time series of NEE is decomposed into 12 intrinsic mode functions (IMF) components and a trend by EEMD

Table 2 Period and variance contribution of NEE, LE in each timescale

Flux	Timescale	Hourly	Diurnal	Weekly	Seasonal	Trend
NEE	IMF	1–3	4–6	7–9	10–12	–
	Period (days)	0.6–0.27	0.6–2.0	4.0–22	50–130	–
	Variance contribution (%)	29.6	58.9	0.6	4.7	6.4
LE	IMF	1–3	4–6	7–9	10–12	–
	Period (days)	0.6–0.33	0.7–2.1	2.9–23	59–250	–
	Variance contribution (%)	15.5	55.2	1.8	5.1	22.4

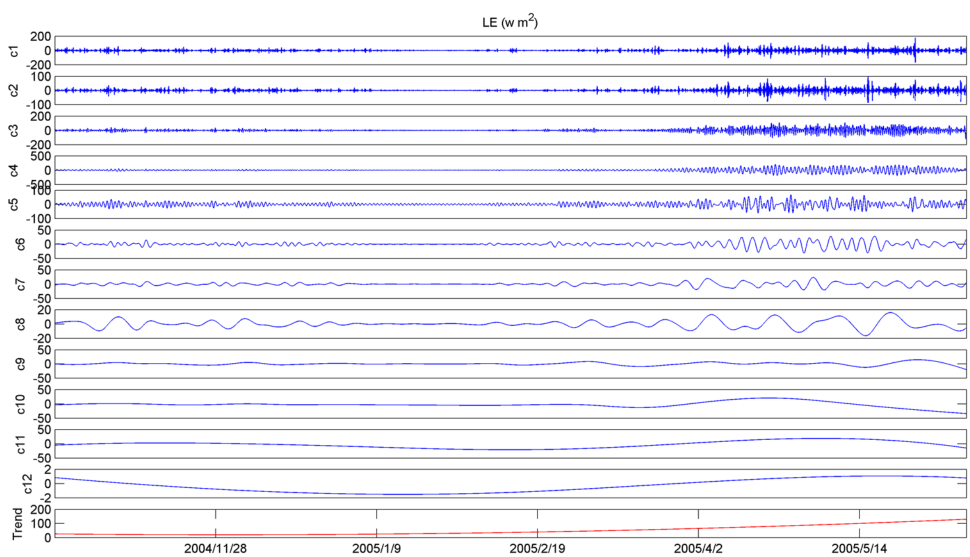

Fig. 3 The time series of LE is decomposed into 12 intrinsic mode functions (IMF) components and a trend by EEMD

evaluated as variance(IMF_i)/$\sum$ variance(IMF_i). Correlation coefficients between IMFs of environmental factors and CO_2 and water flux were calculated to detect those relationships on different temporal scales.

Results

Multiple Temporal Variability of Carbon and Water Exchange

The ecosystem exchange of CO_2 (NEE) is completely decomposed into 12 IMFs and a trend (R) by EEMD

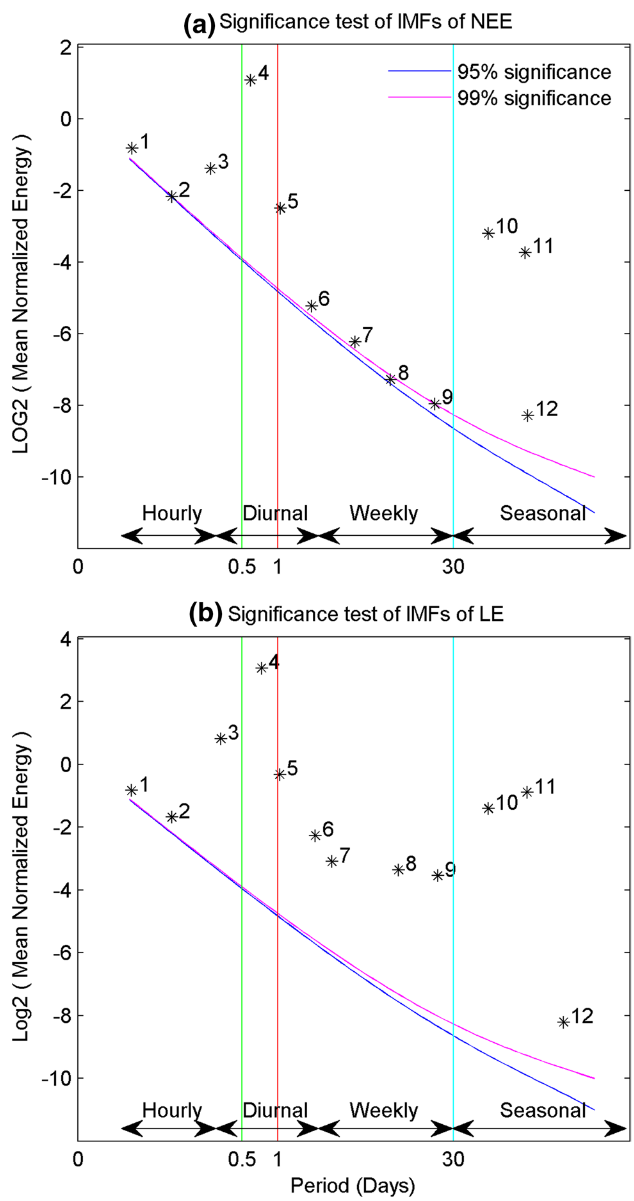

Fig. 4 Significance tests of IMFs of **a** NEE, **b** LE. The upper pink (blue) solid line represents the upper bound of Gaussian noise at 99% (95%) confidence level

(Fig. 2). NEE variations contain 12 quasi-period oscillations on different temporal scales and a trend, which can be classified into four temporal scales (hourly, diurnal, weekly and seasonal) as shown in Table 2. Diurnal and hourly scales are the most significant cycles for NEE variation with 58.9 and 29.6% of variance contribution (Table 2), respectively. The longer scales i.e. weekly and seasonal are weaker than shorter scales with variance contribution of 0.6, 4.7%, respectively.

The LE is also completely decomposed into 12 IMFs and a trend (R) by EEMD (Fig. 3). 12 IMFs indicate water flux oscillates on different temporal scales including hourly, diurnal, weekly and seasonal (Table 2). Diurnal scale is the dominant oscillation in the water flux with largest variance contribution (55.2%, Table 2). The trend and hourly scales comes next with variance contribution of 22.4 and 15.5%, respectively. Weekly and seasonal scales in the water flux are weaker than short scale like the NEE flux.

Significance tests of IMFs of Fc and water flux (LE) are shown in the Fig. 4. All the IMFs are above the 99 or 95% confidence level bounds. There is remarkable peak on the diurnal scale for Fc and LE (Fig. 4), which is consistent with the largest variance contribution in the diurnal scale.

Multiple Temporal Variability of Environmental Variable

Environmental variables also are decomposed into 12 IMFs and a trend. The statistical periods and variance contributions of IMFs and significance tests are shown in Table 3 and Fig. 5, respectively (corresponding IMFs figures are omitted). IMFs of environmental variables significantly oscillate on different scales include hourly, diurnal, weekly and seasonal (Fig. 5; Table 3). However, there are differences in environmental variables. Trend dominates the oscillation in the temperature with 63.4% variance contribution due to increasing trend from winter to summer. Diurnal variation contributes the large variance contribution in R_n (72%), μ (54.2%), VPD (42.2%), T (18.3%) due to solar diurnal rhythm. There are significant hourly variation in R_n (18.3%), μ (15.5%) and VPD (10.2%). However, soil water only varied at longer scale with larger variance contribution of 35.6, 30.1% in seasonal, weekly scale, respectively. The rainfall is much more in summer than winter causes 32% of variance contribution for soil water in trend.

The remarkable peak in the diurnal scale (Fig. 5a–d) also verified the large variance contribution in diurnal scale for T, R_n, μ and VPD. Conversely, There is remarkable peak in longer scale i.e. seasonal (Fig. 5e) indicates soil water oscillate in longer scale because soil water is relative stable in short scale.

The Relationship Between Carbon and Water Flux and Environmental and Biotic Factors

The correlation coefficients of NEE and environmental factor showed that NEE significantly negatively correlated with net irradiation (R_n), VPD, wind speed (μ), temperature (T) and soil water content (SWS) in original data (Fig. 6a). The largest correlation coefficient is net irradiation (− 0.68). In hourly scale, NEE significantly correlated with all environmental factors except for soil water content (SWS), but all correlation coefficients are smaller than 0.3. In daily scale, net irradiation strongest correlated with NEE and the correlation coefficient is larger than 0.7. The temperature and

Table 3 Period and variance contribution of environmental variables in each timescale

Variables	Timescale	Hourly	Diurnal	Weekly	Seasonal	Trend
T	IMF	1–3	4–6	7–9	10–12	–
	Period (days)	0.6–0.33	0.9–3.8	7.0–34.5	110–246	–
	Variance contribution (%)	1.1	18.3	6.2	10.8	63.4
R_n	IMF	1–3	4–6	7–9	10–12	–
	Period (days)	0.6–0.43	0.9–2.0	4.7–19.0	37–233	–
	Variance contribution (%)	18.3	72.0	1.0	1.1	7.6
μ	IMF	1–3	4–6	7–9	10–12	–
	Period	0.6–0.33	0.7–3.1	6.0–25.0	56–278	–
	Variance contribution (%)	15.5	54.2	18.5	7.4	4.3
VPD	IMF	1–3	4–6	7–9	10–12	–
	Period	0.6–0.35	0.9–3.3	6.6–30.0	89–246	–
	Variance contribution (%)	10.2	42.2	7.9	6.1	33.6
SWS	IMF	1–3	4–6	7–9	10–12	–
	Period	0.6–0.23	0.5–2.0	6.7–31.1	74–246	–
	Variance contribution (%)	0.1	2.1	30.1	35.6	32.0

VPD were also strong correlated with NEE (correlation coefficient > 0.4).

NEE significantly correlated with R_n on all timescales, as well as with VPD, T and μ in diurnal scale (Fig. 6a). The soil water content (SWS) impacts NEE on longer scale i.e. the seasonal, which have larger correlation coefficients at seasonal scale, while its smaller values in shorter scale (Fig. 6a) and even insignificantly in hourly scale. The larger coefficient of T, R_n and NEE in seasonal scale indicates the seasonal variation of temperature and solar radiation also influenced the NEE seasonal variation.

LE significantly positively correlated with R_n on all timescales, as well as with VPD and μ in weekly scale (Fig. 6b). The correlation coefficient between LE and soil water become larger from short scale to seasonal scale, which indicates the soil water has little contribution on the LE variation on short scales, but impacts the seasonal variation of LE.

The seasonal variation of NEE and LE also influence by the crop development. By comparing the LAI and the reconstruction of seasonal signals (IMF10 + IMF11 + IMF12) of NEE and LE (Fig. 7), the seasonal IMFs of Fc and LE keep consistent trend with LAI, which implies LAI regulates the CO_2 and water flux in the seasonal scale.

Discussions

The most significant temporal scale is diurnal for R_n due to the daily rhythms in solar radiation. The diurnal cycle of sun causes the diurnal variation of temperature, VPD and wind. However, the soil water is less influenced by solar radiation and keeps stable in the short term scale, which is influenced by the rainfall or irrigation. That is why the variance contribution for soil water in hourly (0.1%) and diurnal (2.1%) scale is very small.

The variability of CO_2 and water flux was investigated at scales ranging from hourly to seasonal using EEMD in winter wheat. The EEMD can successfully diagnose the multiple temporal singles from hourly to seasonal including in the original flux data like the Fourier transformation (Baldocchi et al. 2001), singular system analysis (Mahecha et al. 2007) and wavelet transformation (Katul et al. 2001; Katul and Parlange 1995; Stoy et al. 2005). The variation of diurnal scale dominates the CO_2 and water flux variation in this agriculture ecosystem due to solar rhythm, which also tested in forest (Baldocchi et al. 2001; Stoy et al. 2005), grassland (Stoy et al. 2009) and maize (Ding et al. 2013). Compared with other method (Fourier transformation, wavelet transformation), the trend of CO_2 and water flux can be detected by using EEMD. The variance contribution of LE is 22.4% (Table 2) in trend, which indicates the increasing trend of LE in the winter wheat growing season.

A previous study about wavelet analysis in summer maize in the North China Plain showed the CO_2 and LE flux had significant periods at 110, 64 and 32 day (Qin et al. 2008). Compared with the significant period at long-term scale, our result was different. The most significant variability of CO_2 and LE was at short-term scale, i.e. diurnal scale. We inferred that the noise of CO_2 and LE flux cause the wavelet analysis failed to extract the short-term scale signals. However, EEMD successfully decomposed different temporal signals included in this nonlinear and non-stationary carbon and water flux data.

The CO_2 and water flux is influenced not only by physical but also biological drivers on different temporal scales (Baldocchi and Wilson 2001; Katul et al. 2001; Stoy et al. 2005). In short-term scale such as second and hourly,

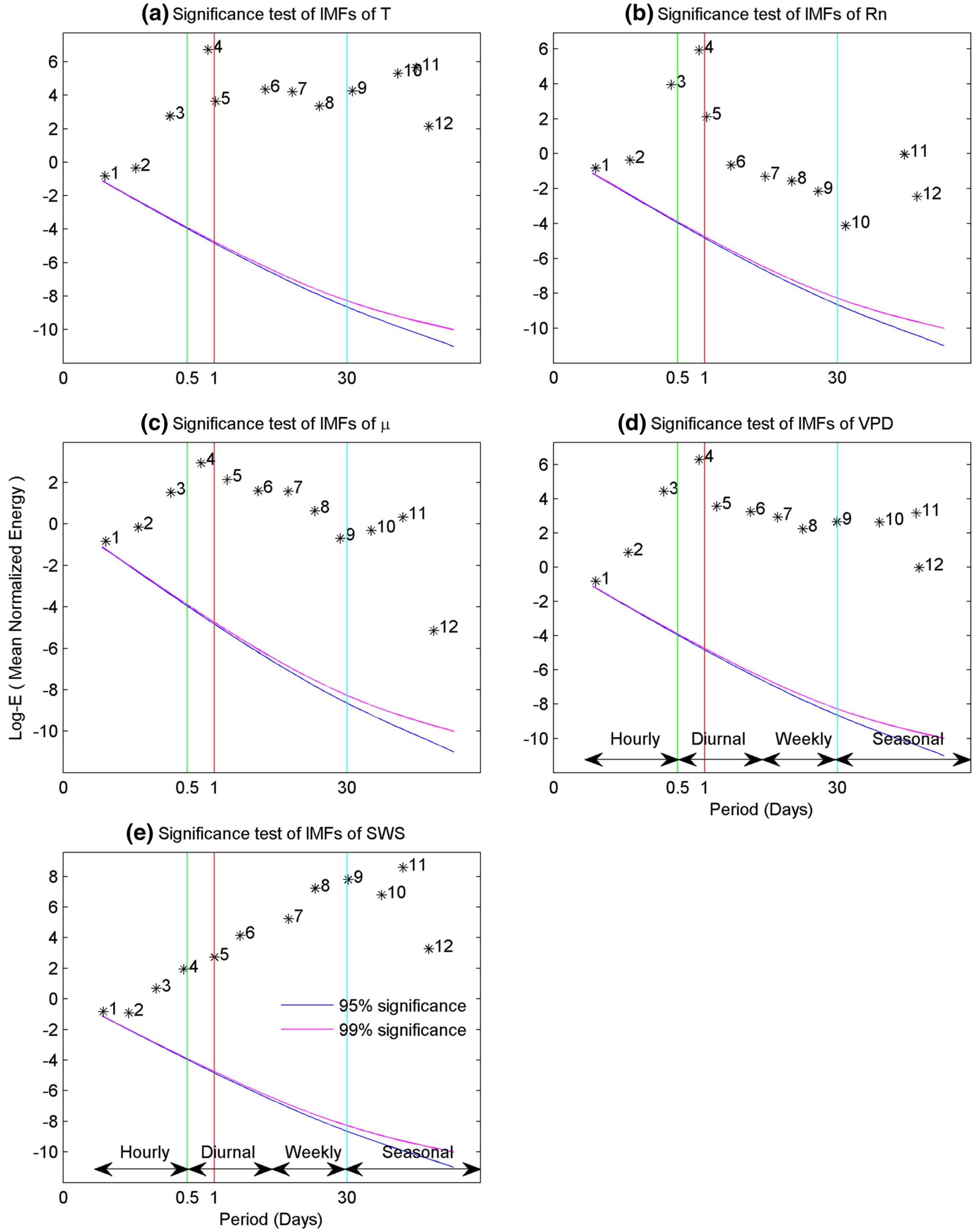

Fig. 5 Significance tests of IMFs of **a** T, **b** R_n, net radiation, **c** μ, wind speed, **d** VPD, **e** θ, soil water. The upper pink (blue) solid line represents the upper bound of Gaussian noise at 99% (95%) confidence level

variation in CO_2 and water exchange are forced by turbulent eddy motion or precipitation events (Katul et al. 2001; Stoy et al. 2005). The high correlation between CO_2 and LE flux and R_n in all timescale provided the evidence that carbon and water flux were primarily regulated by R_n (e.g., the photosynthetic response to solar radiation), which was supported by other studies (Baldocchi et al. 2001; Ding et al. 2013; Stoy et al. 2009). However, in the long-term scales, synoptic weather events and crop phenology regulated variation in carbon and water fluxes

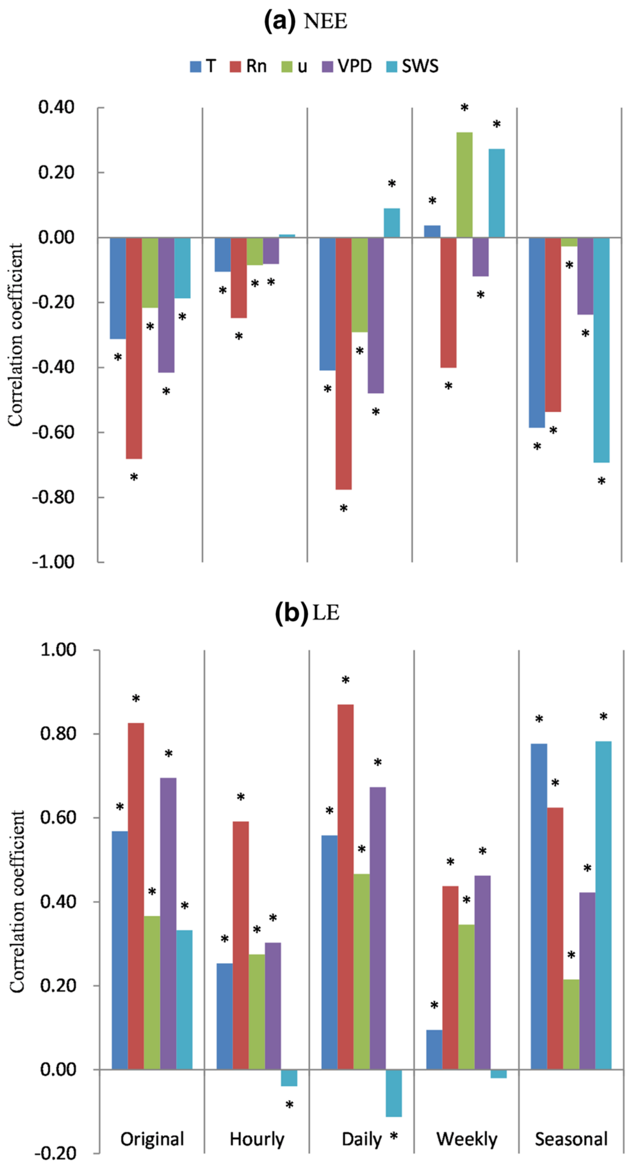

Fig. 6 Correlation coefficients of the flux and environmental variables in different scales. The asterisk indicates significant test of P value is less than 0.05

(Dietze et al. 2011; Stoy et al. 2005). In our study, the soil water more correlated with flux in the seasonal scale. Furthermore, LAI synchronized with the NEE and LE in seasonal scale which justified that the biological control in long-term scale.

Conclusions

This paper attempted to analyze the characteristics of flux and environmental variables on different temporal scales by a new novel tool EEMD and try to unveil how

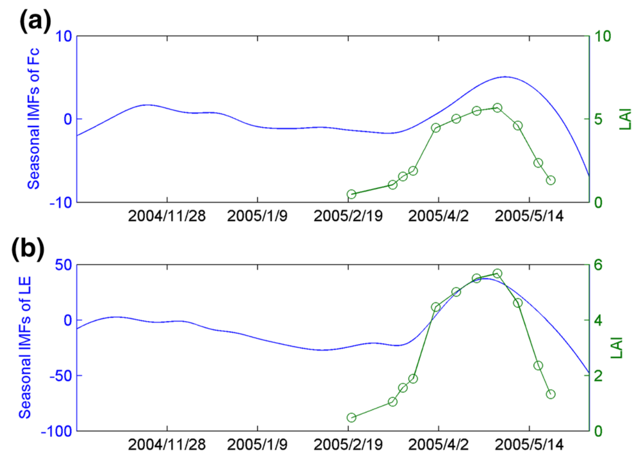

Fig. 7 The comparison of seasonal IMFs (10–12) of **a** NEE, **b** LE and LAI

the environmental and biological factor drive carbon and water flux on multi-temporal scales in winter wheat. The results showed that all environmental and flux variables can be decomposed into different temporal scales including hourly, diurnal, weekly and seasonal scales. The diurnal variations of carbon and water fluxes were regulated by diurnal variation of the net radiation (R_n), VPD and wind speed (μ) due to the daily rhythms in solar radiation. The soil water varied in the longer scale, i.e. seasonal scale due to less variation in short scales and controlled carbon and water fluxes in longer scales. Furthermore, the crop dynamics regulated carbon and water fluxes in the seasonal scale.

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