First Step Toward Bridging Ecological and Socio-Economic Systems: Linking Thermodynamics, Complexity, and Sustainability

Kim, Joon (1); Yun, Juyeol (1); Kwon, Hyojung (2); Chun, Junghwa (3)

(1) Complex Systems Science Laboratory, Department of Landscape Architecture and Rural Systems Engineering, Seoul National University, Seoul 151-921, Korea, joon@snu.ac.kr, mesafalcon0@gmail.com
(2) National Center for AgroMeteorology, Seoul National University, Seoul 151-921, Korea, hyojungkwon@snu.ac.kr
(3) Korea Forest Research Institute, Seoul 130-712, Korea, chunjh69@forest.go.kr

Abstract: Challenges related to achieving sustainable social-ecological systems (SES) are transforming science and its role in society. Over the past few decades, integrated sciences such as sustainability science and complex systems science have emerged as fields of research and education, which transcend disciplinary boundaries and focus on understanding of the dynamics of complex SES. A social-ecological system is a combined system of social and ecological components and drivers that interact and give rise to phenomena, which cannot be understood on the basis of social or ecological considerations alone. A pivotal hinge is therefore needed to bridge social systems and ecological systems. Based on the concepts of openness, directionality, connectivity, and complex dynamics under the framework of nonequilibrium thermodynamics, the state of both systems could be described as process networks of feedback loops and their related time scales. Ruddell and Kumar (2009) argued that such a process network can describe the magnitude and direction of the flow of energy, matter, and information among the different variables in complex, open, dissipative systems. Identification and characterization of such network architecture may provide us with scale-free approaches to integrating system components and drivers having different dimensionality and complexity. As a first step in this direction, we have attempted to delineate such a process network in ecohydrological systems by analysing the multivariate time series data obtained from temperate forest ecosystems in Korea and based on information flow statistics.

Keywords: *sustainability, social-ecological system, complexity, ecohydrological system, process network, information theory, feedback, adaptation*

1. Introduction

Human societies and natural ecosystems bear severe consequences due to an accelerating entropic juggernaut experienced as climate change and global capitalism (Rifkin, 2009). Here, the juggernaut metaphor implies the sacrifice we must pay for dissipating energy, not only by the unstoppable consumptive use of energy resources, but also by living systems for the maintenance of their organization. Non-equilibrium thermodynamics of an open, complex system can best characterize such resources that are flowing in (system entropy decreasing locally) and wastes that are flowing out (environmental entropy increasing globally) (Kleidon and Lorenz, 2005). Systems that exchange mass or energy with their surroundings, and temporarily maintain themselves in a state away from thermodynamic equilibrium as well as a locally reduced level of entropy, are called nonequilibrium systems (Prigogine, 1980). Biological systems and socio-economic systems fall into this category (e.g., Ruth, 2005).

All living systems, including social-ecological systems (SES), are inherently dissipative structures. Therefore, they are subject to the second law of thermodynamics. The term *dissipative structure* denotes self-organizing systems that produce entropy for the maintenance of their order. The first law of thermodynamics (i.e., the law of conservation) states that the total energy of a system is conserved while the second law (i.e., the law of entropy) asserts that the entropy of an isolated system is always increasing. The latter formulates that diabatic processes successively degrade the free energy of an isolated system over time, leading to entropy production. Here, an isolated system is a system in which no exchange of energy, mass, and information occurs with the environment

(Jørgensen *et al*., 2007). In statistical terms, the path toward higher entropy is a transition to more probable states. (Thermodynamics tells us not what *will* happen but what *can* happen.) Boltzmann (1886), who statistically interpreted physical entropy as disorder, wrote that: “the general struggle for existence of animate beings is therefore not a struggle for raw materials – nor for energy which exists in plenty in any body in the form of heat – but a struggle for entropy, which becomes available through the transition of energy from the hot sun to the cold earth.” In an isolated system, the production of entropy eventually results in an equilibrium state of maximum entropy with zero gradient (i.e., thermal death). For this reason, living systems cannot be at the conditions of the thermodynamic equilibrium, but keep themselves as far as possible from that state. In this sense, the fundamental query of physicist Erwin Schrödinger (1944) may be approched by defining life as *living in far-from equilibrium*.

A social-ecological system is a combined system of social and ecological components and drivers that interact and give rise to phenomena, which cannot be understood on the basis of social or ecological considerations alone. It should be noted that both have to do with *networks* and involve *complex systems*, and thus, an infodynamical perspective could provide a framework to connect these two different systems in dimensionality and complexity. Infodynamics (i.e., information dynamics) is a developmental perspective animating information theory by way of thermodynamics, in which information is defined as constraints on entropy production (Salthe, 2003). From this perspective, SES is an energy transformation system that is increasingly constrained by informational array (Jørgensen, 2001). In a non-isolated dissipative system, the second law of thermodynamics takes the form of a continuity equation. Hence, the overall change of entropy of the system is determined from the local increase in entropy within the system, and the entropy flux convergence (i.e., the net flux of entropy across the system boundary) (Kleidon and Lorenz, 2005). In steady state (which is a forced condition far from equilibrium and maintained by a steady input of energy or matter), the production of entropy within the system balances the net entropy flux convergence. The entropy production in SES increases at first, but eventually decreases because growth is limited by senescence, which is considered as a consequence of information overload (Salthe, 2003). Far-from equilibrium, high-gain systems are immature in the infodynamic sense (or in the *fore* loop mode in resilience sense), whereas near equilibrium, low-gain systems are relatively senescent (or in the *back* loop mode) (Salthe, 2003; Walker and Salt, 2006).

From an Earth-system perspective, Michaelian (2011) recently proposed against Darwinian theory of natural selection that excessive photon absorption and transpiration have not been eliminated from plants because their basic thermodynamic function is to increase the global entropy production of the earth system in its interaction with the solar environment. This is achieved by dissipating high energy photons into heat in the presence of water, thereby augmenting the global water, carbon and energy cycles. The very existence of these cycles, as the maestro of natural harmony and diversity makes life possible on Earth. Kumar (2008) also enlightens us that these flows, particularly their *variability*, are the important agents for communicating information across the subsystems in the social-ecological systems, and determining the self-organized, evolutionary path they follow. Wonderfully, these cycles and their *variability* are the hands that weave the fabric of rich life on our planet, and we humans are wrongly altering them in an unprecedented way.

Considering the biological catalysis of the ecohydrological cycle as life’s thermodynamic function, we have attempted an information entropy-based method for the robust analysis of such systems, where feedback is important. Ecohydrological systems can be characterized as open, complex, dissipative systems, consisting of a network of processes over a wide range of scales and involving various feedback loops (Ruddell and Kumar, 2009). Here, complex systems are systems in which large networks of components with no central control and simple rules of operation give rise to complex collective behavior, sophisticated information processing, and adaptation via learning or evolution (Mitchell, 2009). The response of such a complex system to changes and disturbances depends on its particular context, its connections across scales, and its past and current states. How do we then define the state of such a system? How can we handle the different dimensionalities of the variables associated with such a system and its environment? Delineating such networks of feedback loops for ecohydrological systems in monsoon Asia is of great concern and urgently needed (e.g., Hong and Kim, 2011). However, the traditional correlation-based analysis cannot delineate such complex processes with detailed information on directionality and the strength of the coupling between the variables. Following Ruddell and Kumar (2009), we examined dependence among a series of variables measured at the flux towers in KoFlux by quantifying the information flow between the different variables along with the associated time lags. The objective of this study is to test, with the time-series datasets obtained at temperate forest sites in monsoon East Asia having different levels of complexity and heterogeneity, the applicability of information theory to ecohydrological systems. We hope that these efforts will eventually contribute to fulfill the objectives of TERRECO (cf. Tenhunen et al, this proceedings).

2. Methods and Materials

We used Shannon's information entropy as our methodology (Shannon, 1948) and calculated the transfer entropy (*TE*), in order to measure the reduction in the entropy of the current state of a measured variable $X_t^{(j)}$ due to the knowledge of prior state in another variable $X_t^{(i)}$, which is in addition to the information provided by the immediate prior history of $X_t^{(j)}$ (e.g., Ruddell and Kumar, 2009). We normalized *TE* using *m* (set at 11) discrete bins to estimate the probability distribution function. The information flow process network consists of the asymmetric pair wise *TE* between the i^{th} and j^{th} variable from the set of n_v observed variables and is represented as an adjacency matrix (Kumar and Ruddell, 2010).

We used the time series data in 2008 from two adjacent KoFlux tower flux sites (in deciduous and coniferous forests) located in Korea. The description of the sites and the data can be found in AsiaFlux homepage (http://www.asiaflux.net). In this analysis, we selected 15 variables associated with ecohydrologic and biogeochemical processes in forests, which are atmospheric pressure (*PA*), net ecosystem CO_2 exchange (*NEE*), gross primary productivity (*GPP*), ecosystem respiration (*RE*), latent heat flux (*LE*), precipitation (*Precip*), solar radiation (R_g), air temperature (*T*), vapor pressure deficit (*VPD*), soil temperature (T_s), soil water content (*SWC*), sensible heat flux (*H*), canopy temperature (T_c), wind direction (*WD*), and wind speed (*WS*). We computed process networks for each of thirty-six sub-daily time lags between 30 minutes and 18 hours. Our spectral analysis shows that this subdaily time scale explained 30-40% of the variances of the above variables associated with carbon and water cycles, reflecting that this range is an important scale of land-atmosphere interactions. In this process, the complexity and heterogeneity embedded in the observed flux data may hinder the application and interpretation of such information flow statistics. Therefore, estimation and methodological issues were examined by comparing these two adjacent forests with different levels of heterogeneity and complexity.

3. Preliminary Results

The adjacency matrix for the 15 variables results in 210 potential pairwise couplings, about 25% out of which were found to be statistically significant at one or more time lags in May 2008, for example, for both deciduous and coniferous forests. Preliminary results on network matrix are presented in Tables 1-4.

Table 1. Network matrix for mutual information

Gwangneung Forest, 2008 May, GDK(GCK)

AI	PA	NEE	GPP	RE	LE	Precip	Rg	T	VPD	Ts	SWC	H	Tc	WD	WS
PA	*93.5 (94)*	2.7 (3.4)	2.9 (3.5)	12.3 (6.9)	1.9 (2.8)	1.8 (1.8)	4.7 (4.8)	11.8 (9.5)	6.7 (6)	16.3 (-)	14.2 (15.7)	3.8 (5.4)	10.7 (9.9)	5.1 (3.8)	4.9 (6.2)
NEE	2.7 (3.4)	*55.5 (59.6)*	44.2 (47.3)	1.8 (3)	7.3 (6.9)	1.2 (1.3)	11.2 (9.9)	1.9 (2.9)	3.1 (4.3)	2 (-)	2.2 (2.6)	7.9 (8.6)	3 (3.6)	2.4 (3.4)	2.4 (3.6)
GPP	2.9 (3.5)	44.2 (47.3)	*56.4 (57.3)*	2 (1.5)	7.7 (7.3)	1.4 (1.5)	11.7 (11)	2.1 (2.6)	3.7 (4.3)	2.2 (-)	2.1 (2.9)	7.9 (9)	3.2 (3.4)	2.5 (3.6)	2.4 (4)
RE	12.3 (6.9)	1.8 (3)	2 (1.5)	*93.3 (48.5)*	2.5 (1.8)	2.3 (0.8)	4.2 (2.9)	54.6 (23.9)	15.9 (10)	18.7 (-)	8.2 (3.5)	3.1 (2.3)	45.3 (23.3)	2.9 (1.4)	3.4 (1.7)
LE	1.9 (2.8)	7.3 (6.9)	7.7 (7.3)	2.5 (1.8)	*49.6 (63.6)*	0.7 (1.2)	8 (9.8)	3 (3.6)	4.3 (6.3)	2.3 (-)	2.5 (4)	5.3 (9.2)	3.5 (4.1)	2.3 (2.2)	1.5 (4.4)
Precip	1.8 (1.8)	1.2 (1.3)	1.4 (1.5)	2.3 (0.8)	0.7 (1.2)	*15.2 (15.8)*	1.6 (1.5)	2.3 (2.1)	1.6 (1.6)	1.6 (-)	2.5 (3.7)	0.9 (1)	1.9 (2.4)	1.2 (1.2)	0.9 (1.8)
Rg	4.7 (4.8)	11.2 (9.9)	11.7 (11)	4.2 (2.9)	8 (9.8)	1.6 (1.5)	*60.2 (59.2)*	4 (5.1)	6.5 (7.9)	3.9 (-)	3.2 (5.4)	19.8 (21.7)	6.2 (6.3)	4.1 (4.6)	2.6 (6.3)
T	11.8 (9.5)	1.9 (2.9)	2.1 (2.6)	54.6 (23.9)	3 (3.6)	2.3 (2.1)	4 (5.1)	*94.5 (91.1)*	18.5 (15.7)	22.2 (-)	8.5 (8)	3.1 (4.2)	55 (55.3)	2.9 (2.9)	3.1 (3.5)
VPD	6.7 (6)	3.1 (4.3)	3.7 (4.3)	15.9 (10)	4.3 (6.3)	1.6 (1.6)	6.5 (7.9)	18.5 (15.7)	*81.9 (76.8)*	9.7 (-)	7 (5.2)	4.3 (6.2)	18.6 (16.4)	2.8 (2.9)	3.4 (7.3)
Ts	16.3 (-)	2 (-)	2.2 (-)	18.7 (-)	2.3 (-)	1.6 (-)	3.9 (-)	22.2 (-)	9.7 (-)	*96.3 (-)*	13.9 (-)	3.4 (-)	19.5 (-)	3.9 (-)	5.3 (-)
SWC	14.2 (15.7)	2.2 (2.6)	2.1 (2.9)	8.2 (3.5)	2.5 (4)	2.5 (3.7)	3.2 (5.4)	8.5 (8)	7 (5.2)	13.9 (-)	*65.9 (65.7)*	2.7 (5.1)	7.5 (7.9)	3.9 (3)	3.3 (5.1)
H	3.8 (5.4)	7.9 (8.6)	7.9 (9)	3.1 (2.3)	5.3 (9.2)	0.9 (1)	19.8 (21.7)	3.1 (4.2)	4.3 (6.2)	3.4 (-)	2.7 (5.1)	*63.9 (65.3)*	4.9 (4.8)	4.5 (5.6)	2.4 (5.9)
Tc	10.7 (9.9)	3 (3.6)	3.2 (3.4)	45.3 (23.3)	3.5 (4.1)	1.9 (2.4)	6.2 (6.3)	55 (55.3)	18.6 (16.4)	19.5 (-)	7.5 (7.9)	4.9 (4.8)	*93.3 (92.5)*	2.8 (3.2)	3.5 (3.8)
WD	5.1 (3.8)	2.4 (3.4)	2.5 (3.6)	2.9 (1.4)	2.3 (2.2)	1.2 (1.2)	4.1 (4.6)	2.9 (2.9)	2.8 (2.9)	3.9 (-)	3.9 (3)	4.5 (5.6)	2.8 (3.2)	*87.8 (79.1)*	3.2 (4.2)
WS	4.9 (6.2)	2.4 (3.6)	2.4 (4)	3.4 (1.7)	1.5 (4.4)	0.9 (1.8)	2.6 (6.3)	3.1 (3.5)	3.4 (7.3)	5.3 (-)	3.3 (5.1)	2.4 (5.9)	3.5 (3.8)	3.2 (4.2)	*77.9 (74.7)*

Table 1 shows the matrix for the mutual information between pairs of variables at zero time lag. Source variable *X* index *i* is in rows; sink variable *Y* index *j* is in columns. Matrix is symmetric. Italics indicate matrix diagonal. All values are in percent. The values before and with parenthesis are for deciduous (GDK) and coniferous forest (GCK), respectively. Table 2 shows the matrix for the percentage of uncertainty of each Y explained by X (not shown). Table 3 shows the matrix for the ratio of the maximum lag to mutual information for all significant couplings. Table 4 shows time lags of significant information flow on the interval, including the first significant lag, last significant lag, number of significant lags, and peak time lag. Significant lag times are [first-last (number), max].

Table 2. Network matrix for uncertainty percentage (not shown)

Table 3. Network matrix for the ratio of the maximum lag to mutual information

Gwangneung Forest, 2008 May, GDK(GCK)

Atz	PA	NEE	GPP	RE	LE	Precip	Rg	T	VPD	Ts	SWC	H	Tc	WD	WS
PA	x (x)	x (x)	x (x)	x (x)	2.7 (x)	1 (x)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (2.8)	x (x)
NEE	x (x)	0.1 (0.1)	0.1 (0.1)	x (x)	0.7 (1)	1.2 (1.3)	x (x)	x (x)	x (x)	x (-)	x (x)	0.7 (0.7)	x (x)	x (2.2)	x (x)
GPP	x (x)	0.2 (0.2)	0.1 (0.1)	x (x)	0.7 (1)	1.1 (1.1)	x (x)	x (x)	x (x)	x (-)	x (x)	0.7 (0.7)	x (x)	x (2.1)	x (x)
RE	x (x)	x (1.3)	x (2.7)	x (0.1)	2 (2.4)	0.8 (x)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (x)	x (x)
LE	x (x)	0.7 (1)	0.6 (0.8)	x (x)	0.1 (0.1)	1.9 (1.3)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (x)	x (x)
Precip	x (x)	1.5 (x)	1.7 (x)	x (x)	2.3 (x)	0.1 (0.1)	x (x)	x (x)	x (x)	x (-)	1.2 (x)	3.2 (x)	x (x)	x (x)	x (x)
Rg	x (x)	0.7 (0.9)	0.7 (0.8)	x (1.2)	0.7 (0.8)	1.2 (1)	x (x)	x (x)	x (x)	x (-)	x (x)	0.3 (x)	x (x)	x (1.7)	x (x)
T	x (x)	3.4 (x)	x (x)	x (0.2)	x (x)	0.8 (1.1)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (x)	x (x)
VPD	x (x)	2 (1.6)	1.7 (1.6)	x (x)	1.3 (1.1)	1.2 (1)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (3.2)	x (x)
Ts	x (-)	3.5 (-)	x (-)	x (-)	2.5 (-)	1.3 (-)	x (-)	x (-)	x (-)	x (-)	x (-)	x (-)	x (-)	x (-)	x (-)
SWC	x (x)	x (2.2)	x (2.1)	x (x)	x (1.6)	0.8 (0.6)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (2.9)	x (x)
H	x (x)	0.8 (0.8)	0.8 (0.8)	x (1.5)	0.9 (0.8)	2.3 (1.8)	x (x)	x (x)	x (x)	x (-)	x (x)	0.1 (x)	x (x)	x (x)	x (x)
Tc	x (x)	2.1 (1.9)	x (x)	x (0.2)	1.4 (x)	1 (0.8)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (x)	x (x)
WD	x (x)	2.7 (2.1)	2.6 (1.9)	x (x)	2.2 (3.2)	1.8 (1.5)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (0.1)	x (x)
WS	x (x)	x (x)	x (x)	x (2.1)	x (x)	1.8 (x)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (x)	x (x)

Table 4. Network matrix for time lags of significant information flow on the interval

Gwangneung Forest, 2008 May, GDK(GCK)

Tau	PA	NEE	GPP	RE	LE	Precip	Rg	T	VPD	Ts	SWC	H	Tc	WD	WS
PA	x (x)	x (x)	x (x)	x (x)	1-33(10)32 (x)	1-7(4)7 (x)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (7-7(1)7)	x (x)
NEE	x (x)	2-8(7)3 (2-9(8)2)	2-9(8)3 (2-9(8)4)	x (x)	1-10(9)2 (1-8(8)3)	1-32(10)2 (2-16(2)16)	x (x)	x (x)	x (x)	x (-)	x (x)	1-7(5)1 (2-2(1)2)	x (x)	x (3-5(3)3)	x (x)
GPP	x (x)	2-8(7)3 (2-9(8)2)	2-9(8)3 (2-9(8)4)	x (x)	1-10(9)2 (1-9(9)3)	1-12(8)3 (2-16(3)16)	x (x)	x (x)	x (x)	x (-)	x (x)	1-7(5)3 (3-3(1)3)	x (x)	x (2-5(4)3)	x (x)
RE	x (x)	x (1-33(5)25)	x (25-36(6)32)	x (2-6(5)2)	36-36(1)36 (30-36(4)30)	1-5(4)1 (x)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (x)	x (x)
LE	x (x)	1-6(6)2 (1-8(8)1)	1-6(6)2 (1-8(7)1)	x (x)	2-9(7)2 (2-9(8)3)	1-36(7)36 (1-11(3)11)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (x)	x (x)
Precip	x (x)	1-1(1)1 (x)	2-36(2)36 (x)	x (x)	12-12(1)12 (x)	2-12(8)3 (2-7(5)3)	x (x)	x (x)	x (x)	x (-)	1-1(1)1 (x)	33-36(4)36 (x)	x (x)	x (x)	x (x)
Rg	x (x)	1-36(10)1 (1-9(9)1)	1-36(9)3 (1-36(9)1)	x (19-26(7)24)	1-9(9)1 (1-9(9)3)	1-34(17)6 (1-9(6)6)	x (x)	x (x)	x (x)	x (-)	x (x)	1-4(4)1 (x)	x (x)	x (1-4(2)4)	x (x)
T	x (x)	4-4(1)4 (x)	x (x)	x (1-6(6)2)	x (x)	1-6(4)5 (1-4(3)1)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (x)	x (x)
VPD	x (x)	2-36(4)36 (1-36(7)34)	32-36(5)32 (1-36(6)35)	x (x)	1-36(7)36 (1-36(4)36)	1-30(9)1 (2-3(2)3)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (28-36(5)28)	x (x)
Ts	x (-)	35-35(1)35 (-)	x (-)	x (-)	1-36(31)11 (-)	1-6(6)5 (-)	x (-)	x (-)	x (-)	x (-)	x (-)	x (-)	x (-)	x (-)	x (-)
SWC	x (x)	x (1-8(7)6)	x (1-29(15)1)	x (x)	x (1-9(6)3)	1-36(36)6 (1-31(30)18)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (4-4(1)4)	x (x)
H	x (x)	1-7(7)1 (1-7(7)3)	1-7(7)6 (1-7(7)4)	x (17-23(5)18)	1-8(8)3 (1-6(6)4)	1-15(14)9 (5-19(4)19)	x (x)	x (x)	x (x)	x (-)	x (x)	2-4(3)2 (x)	x (x)	x (x)	x (x)
Tc	x (x)	3-4(2)3 (4-7(2)7)	x (x)	x (1-5(5)1)	1-2(2)1 (x)	1-6(6)1 (1-2(2)1)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (x)	x (x)
WD	x (x)	2-31(3)31 (1-10(8)1)	18-35(5)32 (1-15(7)1)	x (x)	1-27(10)20 (1-9(6)1)	1-35(25)31 (3-17(5)3)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (2-3(2)2)	x (x)
WS	x (x)	x (x)	x (x)	x (23-23(1)23)	x (x)	3-5(2)5 (x)	x (x)	x (x)	x (x)	x (-)	x (x)	x (x)	x (x)	x (x)	x (x)

Figure 1 shows an exemplary arrangement of subsystems, information flow, feedback, and time scales that define the May 2008 state of the ecohydrological system. Subsystems are defined as a group of variables, which are structurally equivalent such that they share a common role in the larger system structure. They are aggregations of individual nodes that share similar patterns of coupling type and time scale. Nodes in the same subsystem should share synchronization-dominated couplings. Forcing or uncoupled-dominated couplings mean that coupled nodes do not belong to the same subsystem. As seen in Fig. 1, a self-organizing *turbulent* subsystem was formed from *H*, *LE*, *NEE* and *GPP*, which share *feedback* couplings at < 1-2 hr time scale. A *synoptic* subsystem was formed from *VPD*, T_c, *T*, *RE* and *SWC*, which share *synchronization*, serving as a large-scale forcing to other subsystems. An *atmospheric boundary layer* (ABL) subsystem was formed; and the self-organizations via hierarchical aggregations at regional scale were identified, as indicated by Ruddell and Kumar (2009). Furthermore, disappearance of such regional self-organizing subsystems that bind the turbulent and ABL subsystems at longer time scales were also observed during the dry spell in spring and the summer monsoon season.

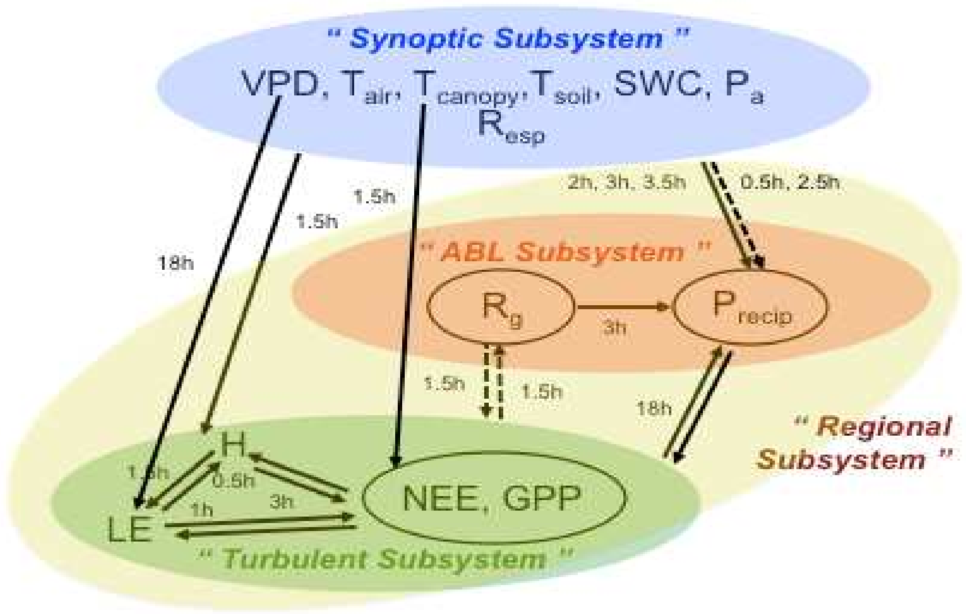

Figure 1. The process network for May 2008, an arrangement of subsystems, information flow, feedback, and time scales that define the state of the ecohydrological system in Gwangneung deciduous forest in Korea.

Despite the complexity and heterogeneity that were imbedded in the field observation data obtained at GDK site, we were able to delineate process networks from multivariate time series data by using information flow statistics as suggested by Ruddell and Kumar (2009). Simultaneous consideration of mutual information (measure of synchronization) and transfer entropy (cause of synchronization) enabled us to identify the differences between two states of the ecohydrological system on the basis of variations in the pattern of feedback coupling on the network. Further analysis and scrutiny are currently in progress.

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