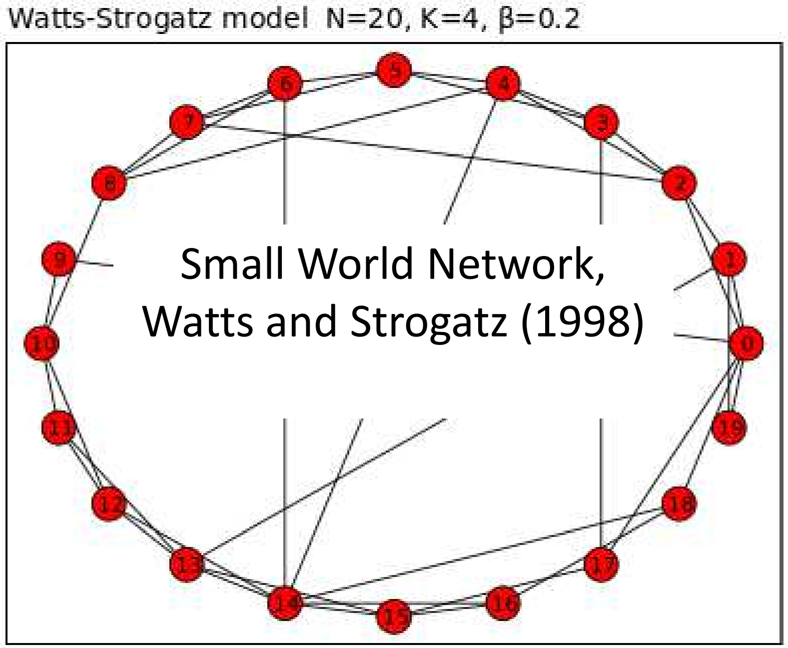
Climate sensitivity of global terrestrial ecosystems' subdaily carbon, water, and energy dynamics (an application of information flow process networks)

Workshop on Information Theory in the Geosciences
Schneefernerhaus, Zugspitze, Germany
April 24-28, 2016

Macrosystems Biology Grant 2013-#1241960 (Conclusions are those of the authors and not necessarily the NSF)

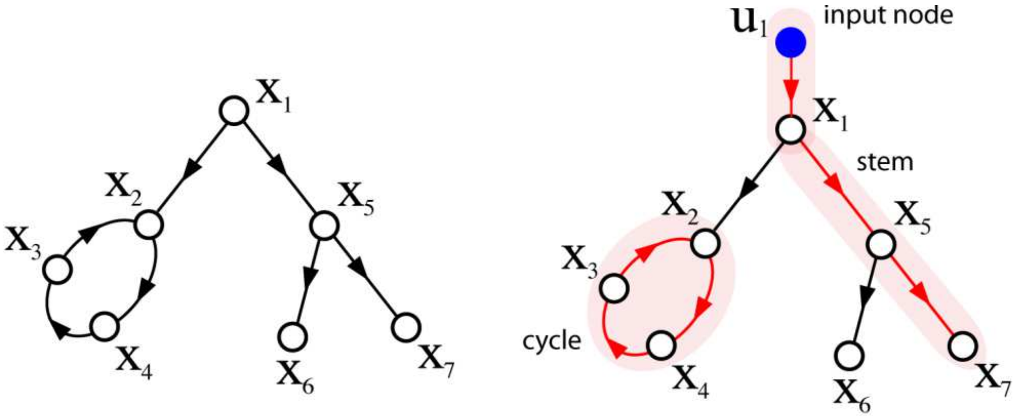
Benjamin L. Ruddell, bruddell@asu.edu
Dan Childers
Rong Yu
Minseok Kang
Joon Kim

Classic Network Theory Applications (are limited)

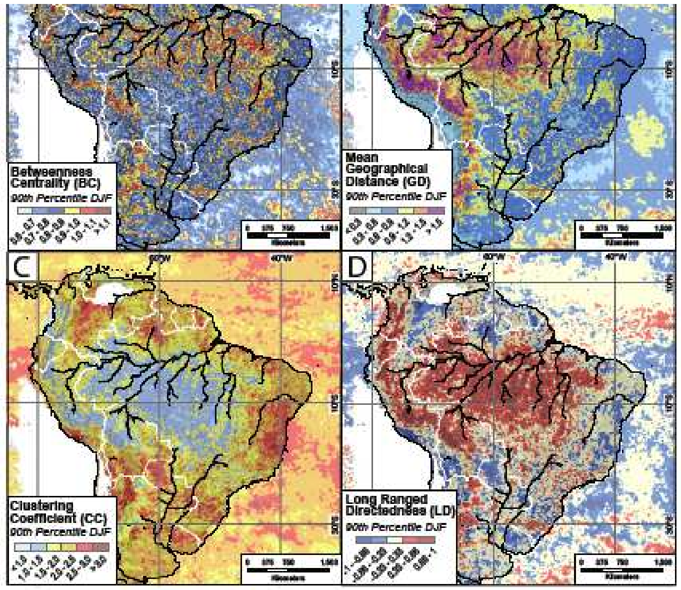


Small World Network, Watts and Strogatz (1998)

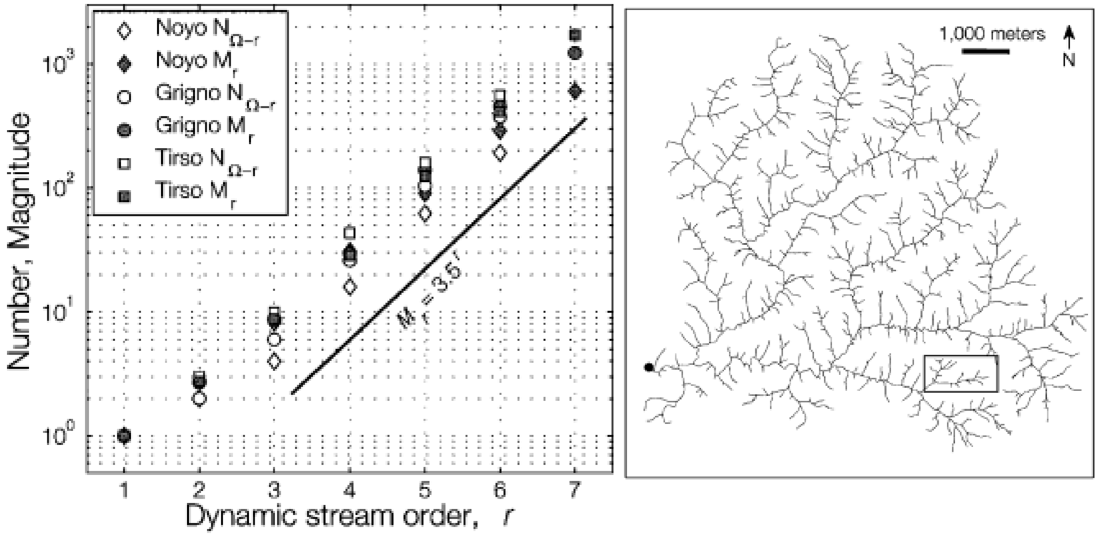
Control Centrality, Liu et al. (2012)



Betweenness Centrality for Amazon Rainfall, Boers et al. (2013)



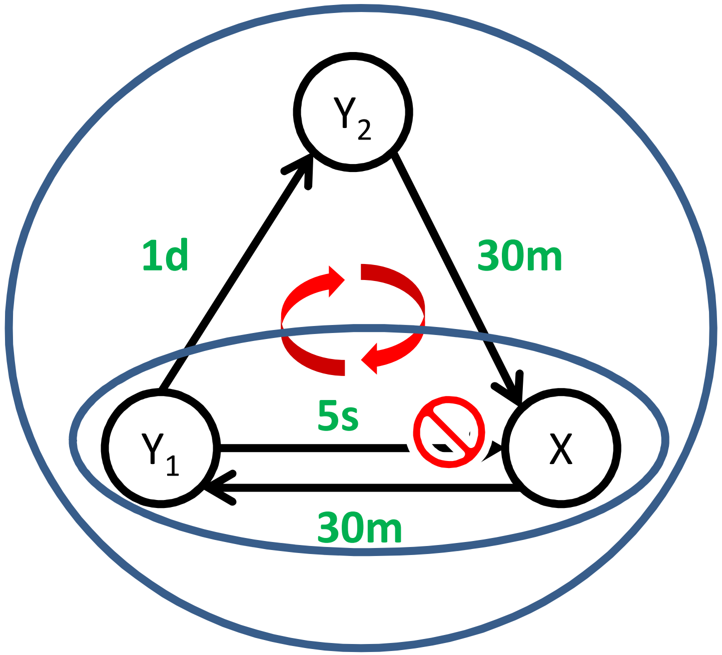
River Basin Power Law Scaling, Zaliapin et al. (2010)



Process Networks

<u>Complex systems</u> generally feature coupling and *feedback* between many nodes, producing self-organizing subsystem behavior, and/or *thresholds* where key couplings turn on and off and qualitatively different system states emerge (Kumar 2007, Liu et al. 2007).

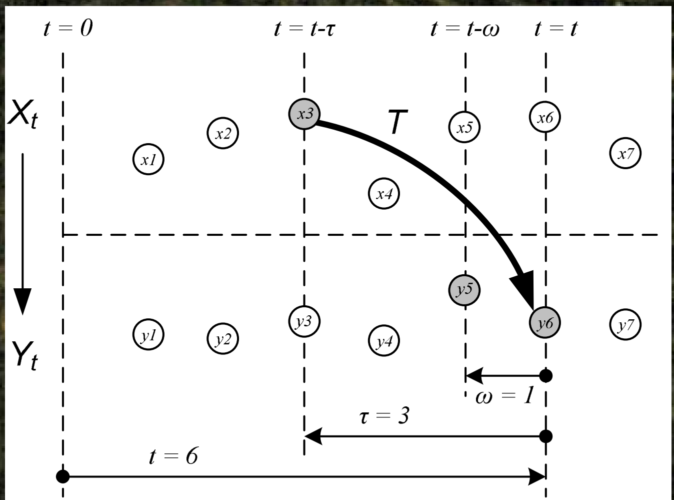
- Hierarchies of self-organizing subsystems can emerge via feedback.
- Connections have characteristic timescales at which processes operate.
- Connections have a *type, direction,* and *strength* (and possibly follow rules)
- In a *multitype network,* connections and nodes may be qualitatively different.

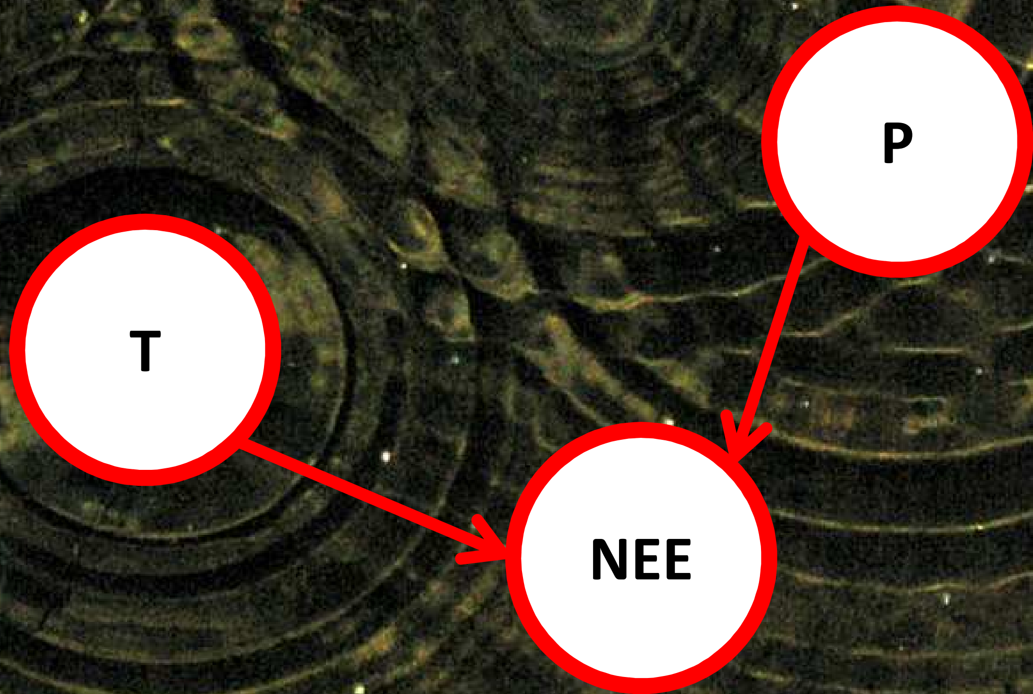


A ***Process Network (PN)*** is a network of feedback loops and the associated timescales that depicts the magnitude and direction of flow between the different subsystems. The PN graph itself defines the system state. (Ruddell and Kumar, 2009a)

We can robustly observe short-timescale dynamical sensitivity of ecosystems to climate forcings using advanced statistics to infer DYNAMICAL PROCESS NETWORKS. (Transfer Entropy, Schreiber 2000)

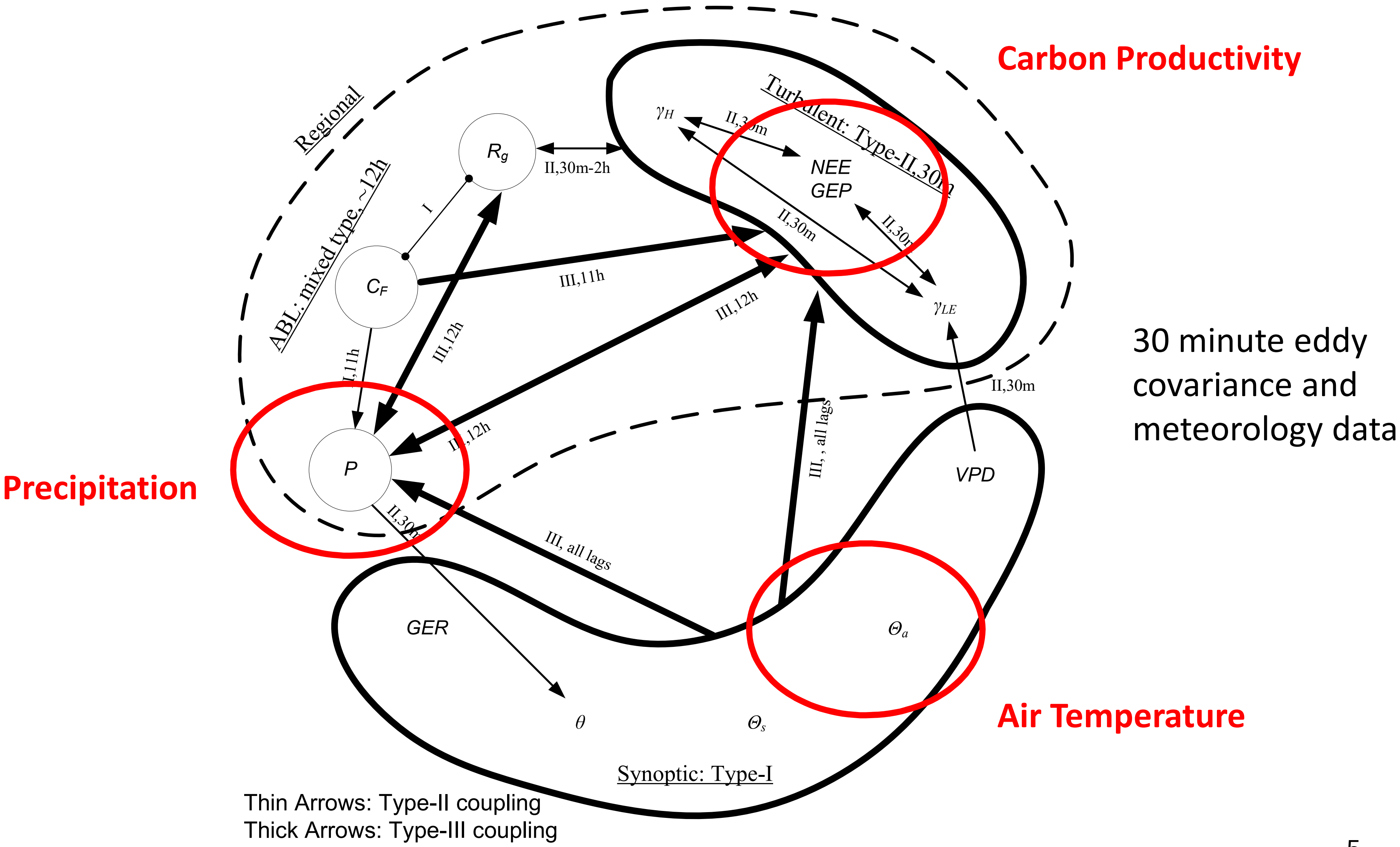
$$T(X_t > Y_t, \tau) = \sum_{y_t, y_{t-1}, x_{t-\tau}} p(y_t, y_{t-1}, x_{t-\tau}) \log \frac{p(y_t \mid (y_{t-1}, x_{t-\tau}))}{p(y_t \mid y_{t-1})}$$



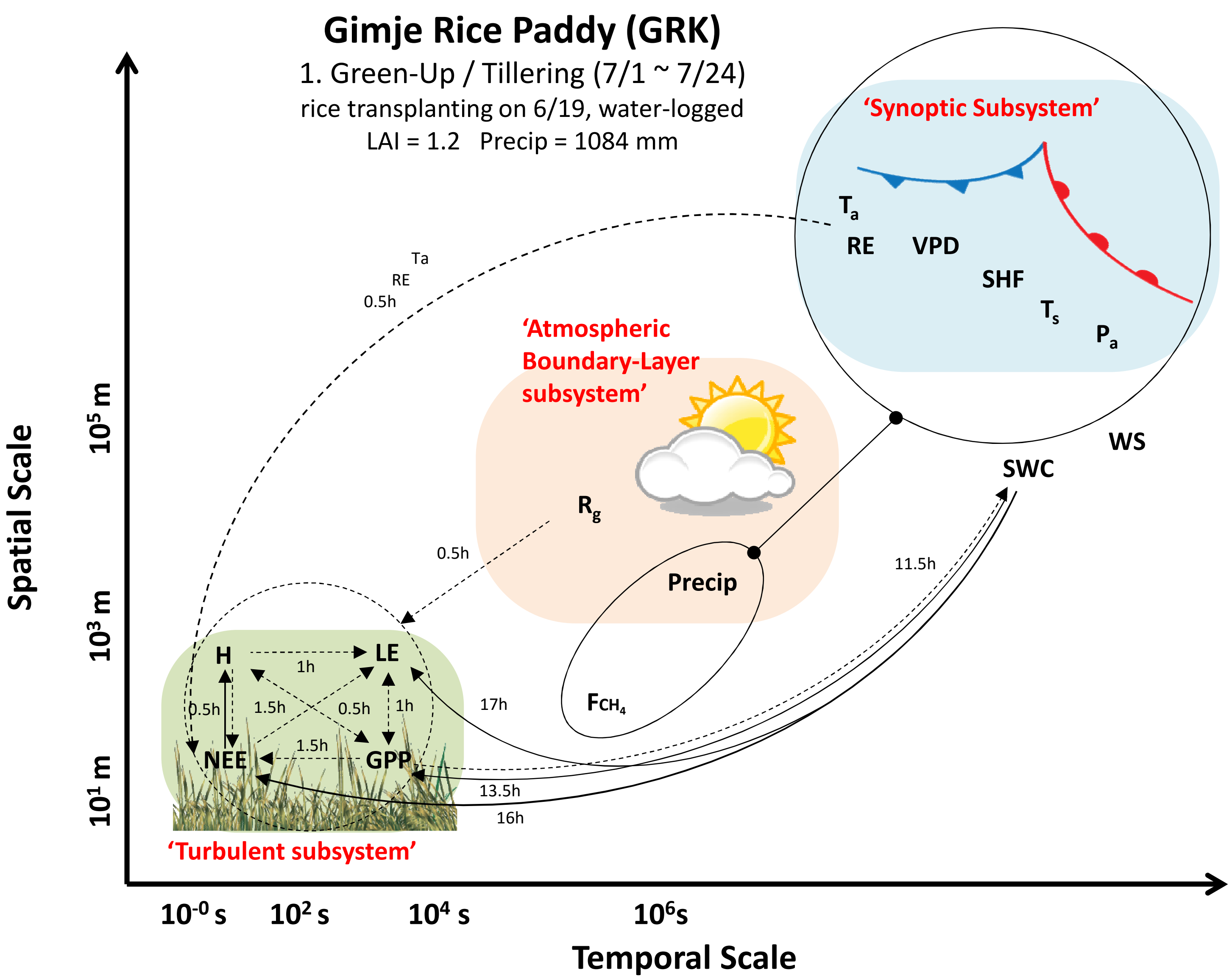


A Dynamical Process Network (DPN) for Illinois Corn+Climate

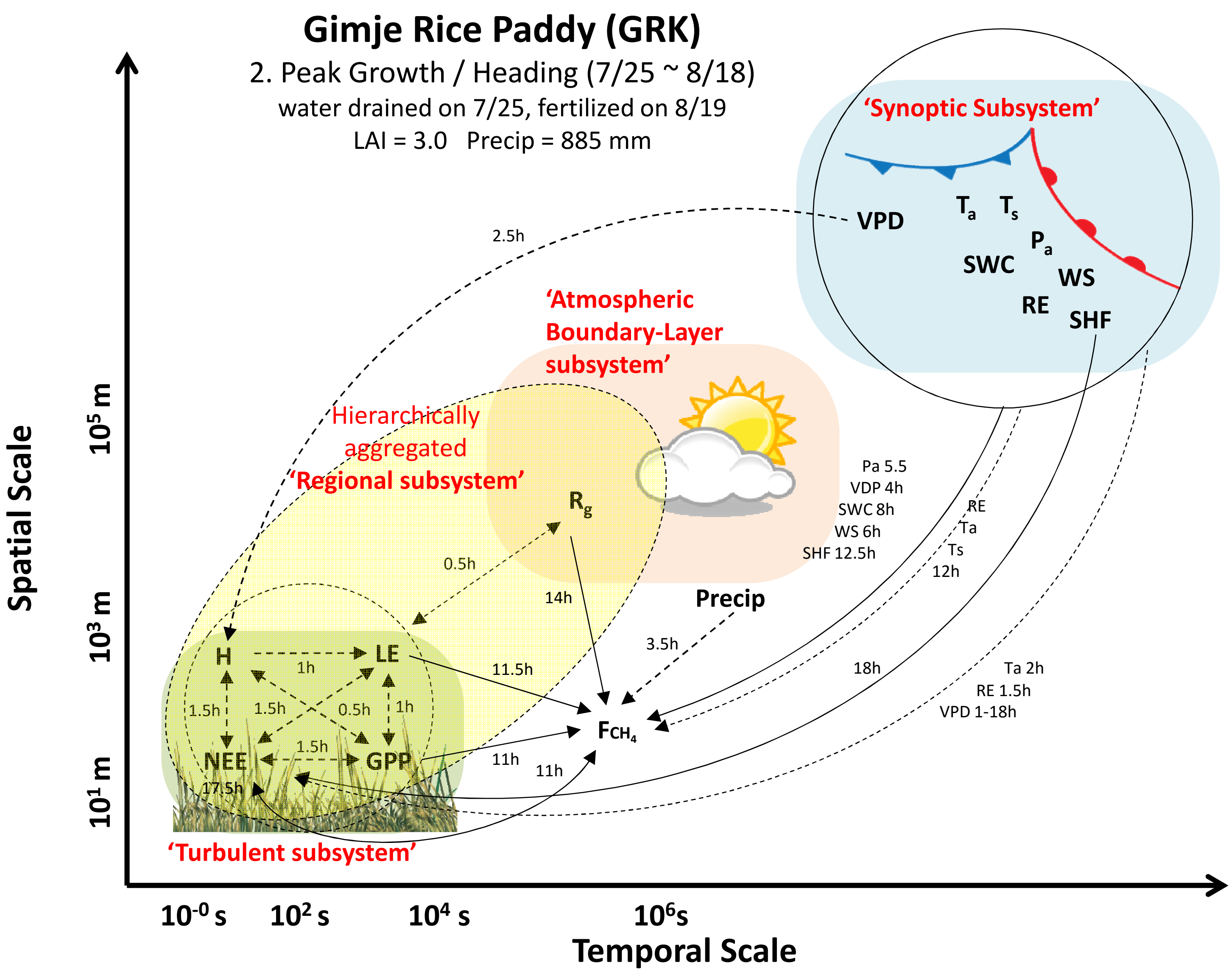
(a graph-based state based on ‘fast’ functional dynamics)

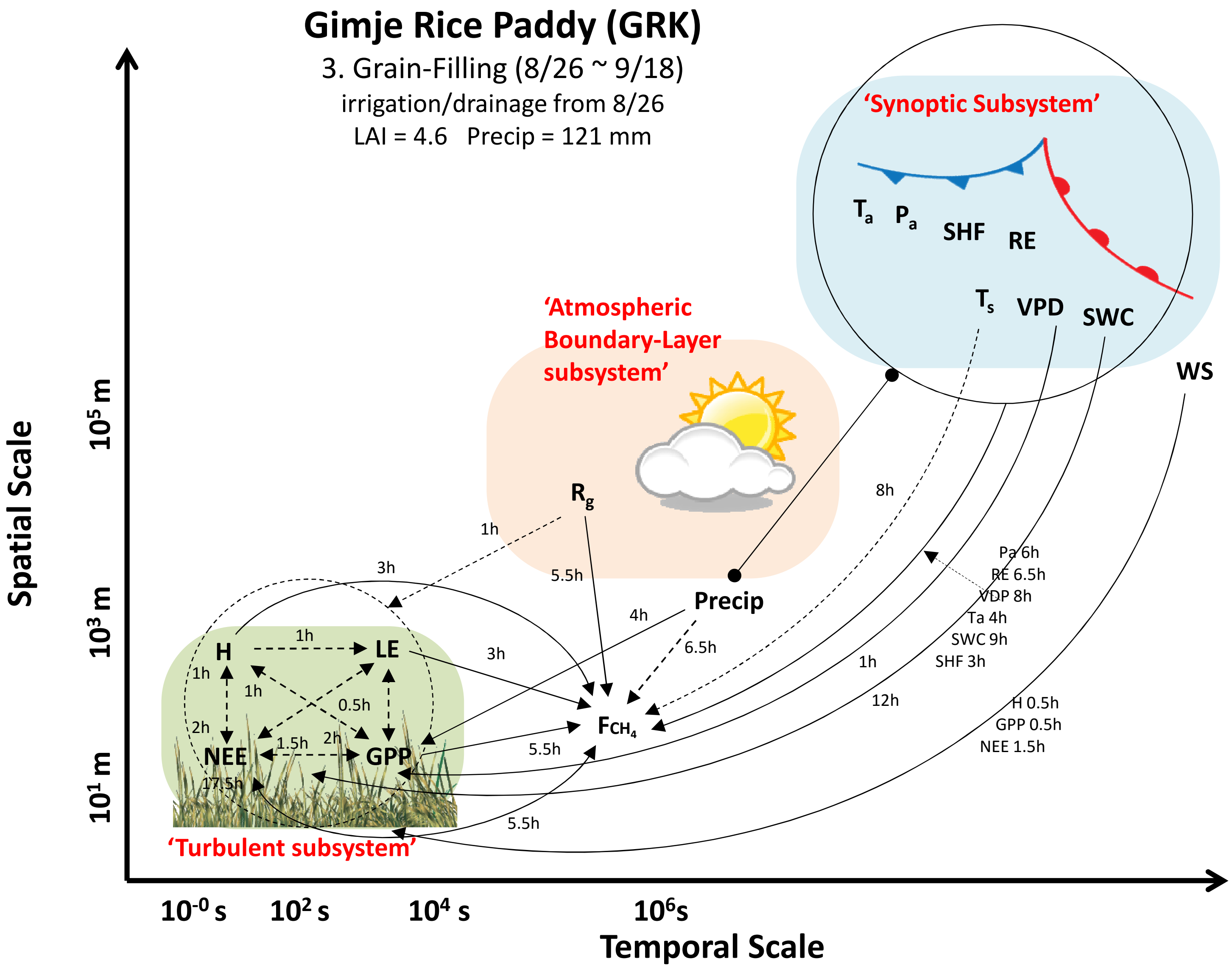


30 minute eddy covariance and meteorology data

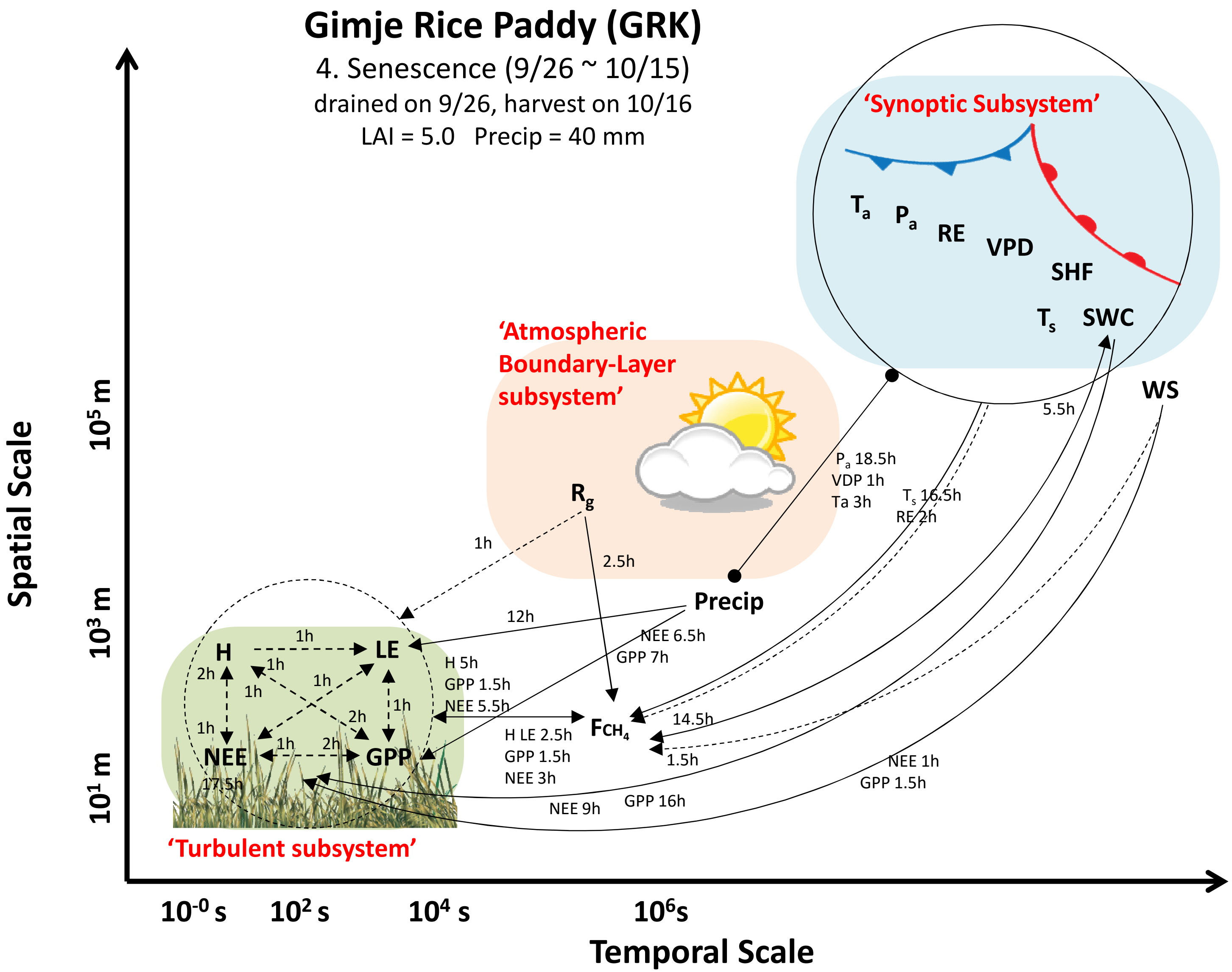


Gimje Rice Paddy (GRK)
1. Green-Up / Tillering (7/1 ~ 7/24)
rice transplanting on 6/19, water-logged
LAI = 1.2 Precip = 1084 mm
'Synoptic Subsystem'
T_a
RE
VPD
SHF
T_s
P_a
WS
SWC
Ta
RE
0.5h
'Atmospheric Boundary-Layer subsystem'
R_g
0.5h
Precip
F_{CH_4}
11.5h
17h
H
LE
1h
0.5h
1.5h
0.5h
1h
NEE
GPP
1.5h
13.5h
16h
'Turbulent subsystem'
Spatial Scale
10^5 m
10^3 m
10^1 m
10^{-0} s
10^2 s
10^4 s
10^6s
Temporal Scale

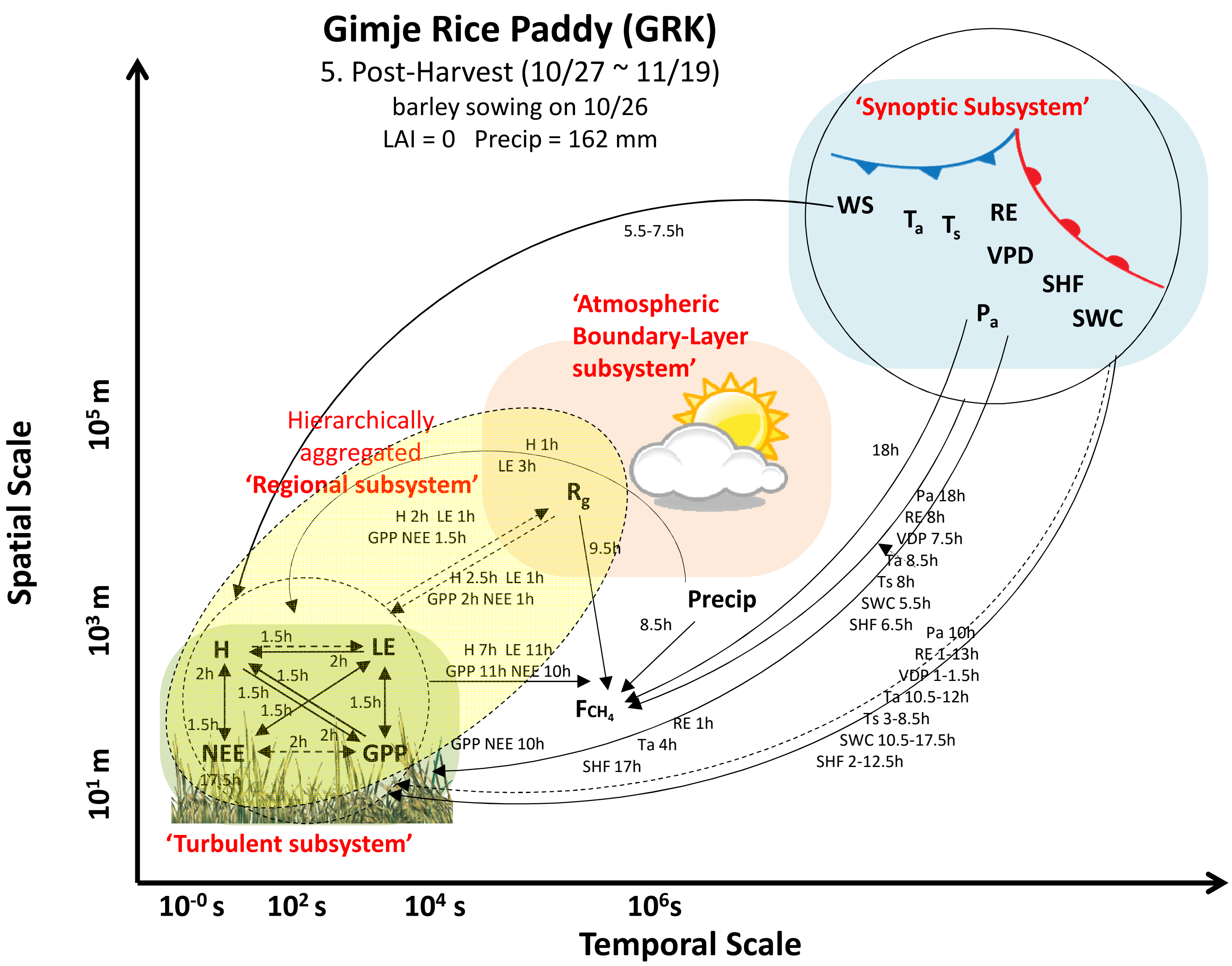

Gimje Rice Paddy (GRK)
2. Peak Growth / Heading (7/25 ~ 8/18)
water drained on 7/25, fertilized on 8/19
LAI = 3.0 Precip = 885 mm
'Synoptic Subsystem'
VPD
T_a T_s
P_a
SWC
WS
RE
SHF
2.5h
'Atmospheric Boundary-Layer subsystem'
Hierarchically aggregated
'Regional subsystem'
R_g
0.5h
14h
Precip
3.5h
Pa 5.5
VDP 4h
SWC 8h
WS 6h
SHF 12.5h
RE
Ta
Ts
12h
18h
Ta 2h
RE 1.5h
VPD 1-18h
H
LE
1h
1.5h
1.5h
0.5h
1h
1.5h
NEE
GPP
17.5h
11.5h
11h
11h
F_{CH_4}
'Turbulent subsystem'
Spatial Scale
10^5 m
10^3 m
10^1 m
10^{-0} s
10^2 s
10^4 s
10^6s
Temporal Scale



Gimje Rice Paddy (GRK)
3. Grain-Filling (8/26 ~ 9/18)
irrigation/drainage from 8/26
LAI = 4.6 Precip = 121 mm
'Synoptic Subsystem'
T_a
P_a
SHF
RE
T_s
VPD
SWC
WS
'Atmospheric Boundary-Layer subsystem'
R_g
Precip
F_{CH_4}
'Turbulent subsystem'
H
LE
NEE
GPP
1h
3h
5.5h
4h
6.5h
8h
12h
17.5h
2h
1.5h
0.5h
Pa 6h
RE 6.5h
VDP 8h
Ta 4h
SWC 9h
SHF 3h
H 0.5h
GPP 0.5h
NEE 1.5h
Spatial Scale
10^1 m
10^3 m
10^5 m
Temporal Scale
10^{-0} s
10^2 s
10^4 s
10^6s

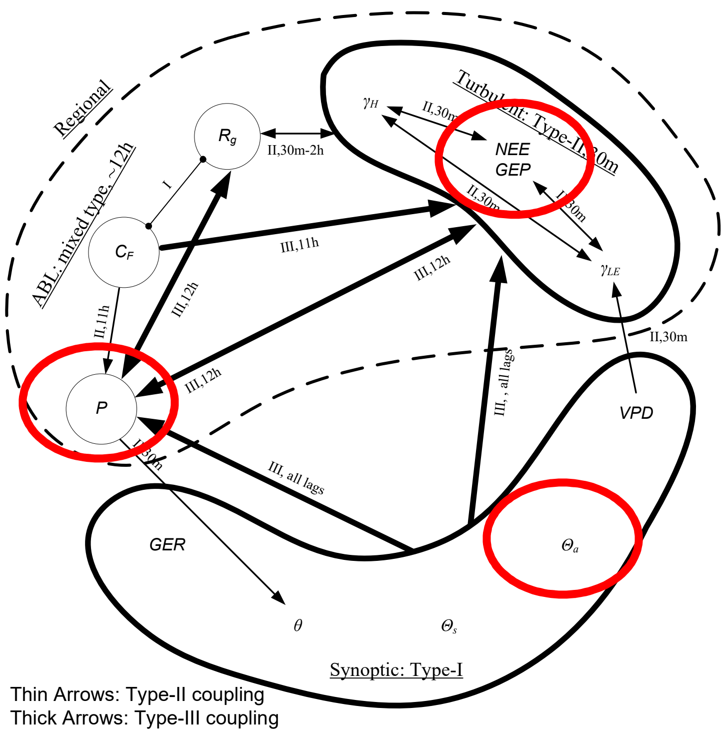


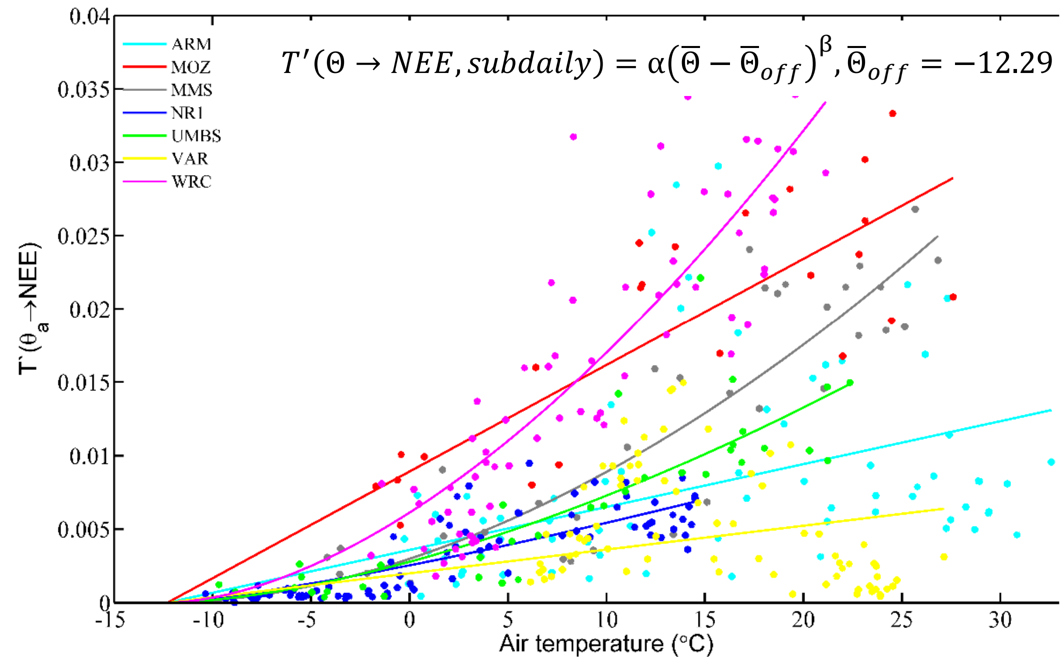
Gimje Rice Paddy (GRK)
4. Senescence (9/26 ~ 10/15)
drained on 9/26, harvest on 10/16
LAI = 5.0 Precip = 40 mm
'Synoptic Subsystem'
T_a P_a RE VPD SHF
T_s SWC
'Atmospheric Boundary-Layer subsystem'
R_g
Precip
WS
'Turbulent subsystem'
H LE NEE GPP
F_{CH_4}
P_a 18.5h
VDP 1h
Ta 3h
T_s 16.5h
RE 2h
5.5h
1h
2.5h
12h
NEE 6.5h
GPP 7h
H 5h
GPP 1.5h
NEE 5.5h
H LE 2.5h
GPP 1.5h
NEE 3h
14.5h
1.5h
NEE 1h
GPP 1.5h
NEE 9h
GPP 16h
17.5h
Spatial Scale
10^1 m
10^3 m
10^5 m
Temporal Scale
10^{-0} s
10^2 s
10^4 s
10^6s

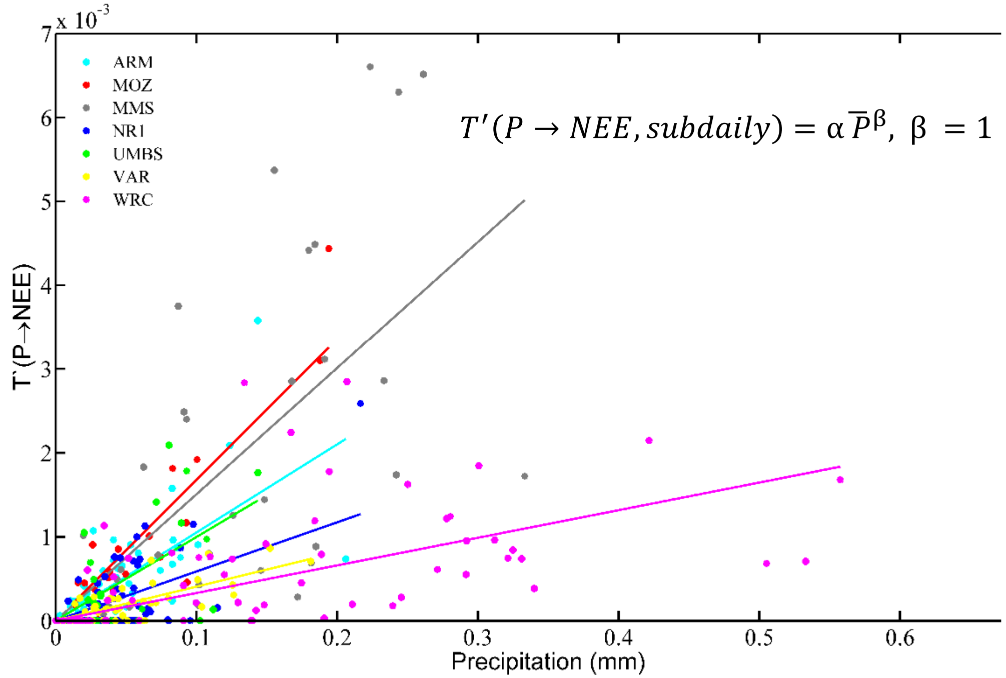

Gimje Rice Paddy (GRK)
5. Post-Harvest (10/27 ~ 11/19)
barley sowing on 10/26
LAI = 0   Precip = 162 mm
'Synoptic Subsystem'
WS
T_a
T_s
RE
VPD
SHF
P_a
SWC
5.5-7.5h
'Atmospheric Boundary-Layer subsystem'
Hierarchically aggregated
'Regional subsystem'
H 1h
LE 3h
R_g
H 2h LE 1h
GPP NEE 1.5h
9.5h
H 2.5h LE 1h
GPP 2h NEE 1h
Precip
8.5h
18h
Pa 18h
RE 8h
VDP 7.5h
Ta 8.5h
Ts 8h
SWC 5.5h
SHF 6.5h
Pa 10h
RE 1-13h
VDP 1-1.5h
Ta 10.5-12h
Ts 3-8.5h
SWC 10.5-17.5h
SHF 2-12.5h
H 7h LE 11h
GPP 11h NEE 10h
F_{CH_4}
RE 1h
Ta 4h
SHF 17h
GPP NEE 10h
H
LE
NEE
GPP
1.5h
2h
1.5h
2h
1.5h
1.5h
1.5h
1.5h
2h
2h
17.5h
'Turbulent subsystem'
Spatial Scale
10^5 m
10^3 m
10^1 m
10^{-0} s
10^2 s
10^4 s
10^6s
Temporal Scale

Elasticity of DPN Information Flows to "slow" forcing factors is often exponential

2003 July: Healthy System State







An Experimental Approach for Ecosystem Change

- ‘Slow’ Dynamics define **SYSTEM STATE** (or ‘macrostate’)
- To robustly predict long-term ecosystem change we need to observe **LONG TERM DYNAMICS OF STATE CHANGE**, but we don’t (yet) have data (paleo?)
- We can however observe the rich **SHORT TERM ‘FAST’ DYNAMICS** of function and structure of the subsystems within each macrostate (the Process Networks)
- By modeling (marginal) changes in those Process Networks as an **ELASTIC RESPONSE** to (marginal) changes in ‘slow’ forcing factors, we have the capability to estimate the response of ecosystem state (and process) to changes in forcings.

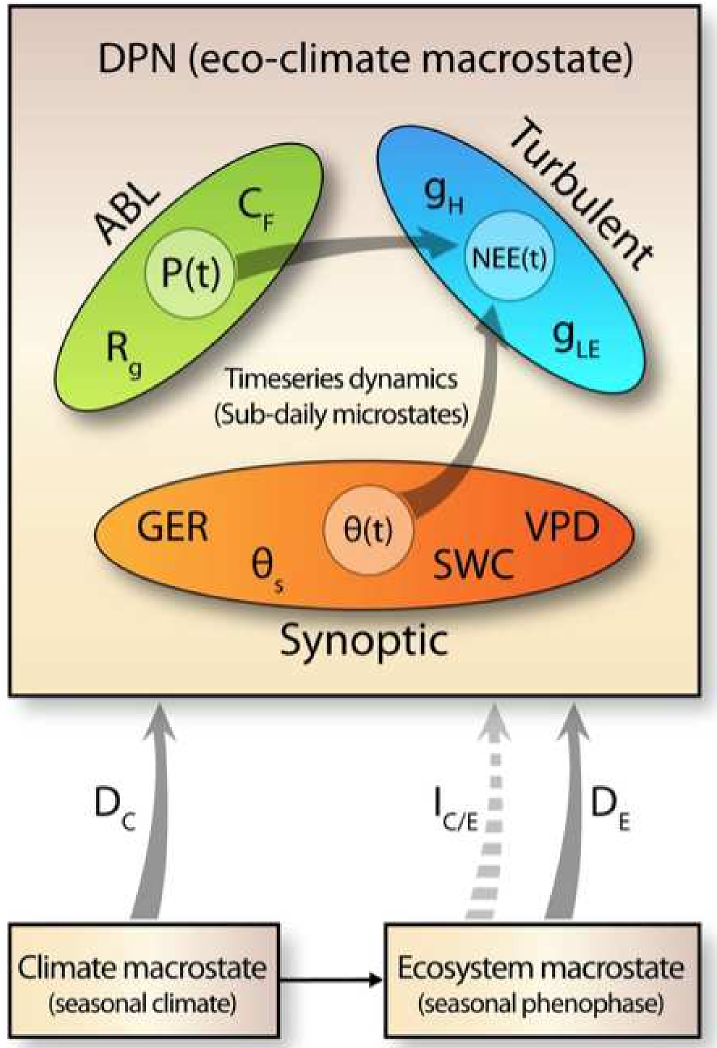
We find that Process Network Elasticity to ‘slow’ forcing factors can often be modeled using exponential functions derived from econometrics; these also separate combined and indirect effects.

Seasonal “slow” Forcing Factors are:

- Temperature
- Radiation
- Precipitation
- EVI/phenophase

Optimize for coefficients using OLS

Coefficients are the elasticities

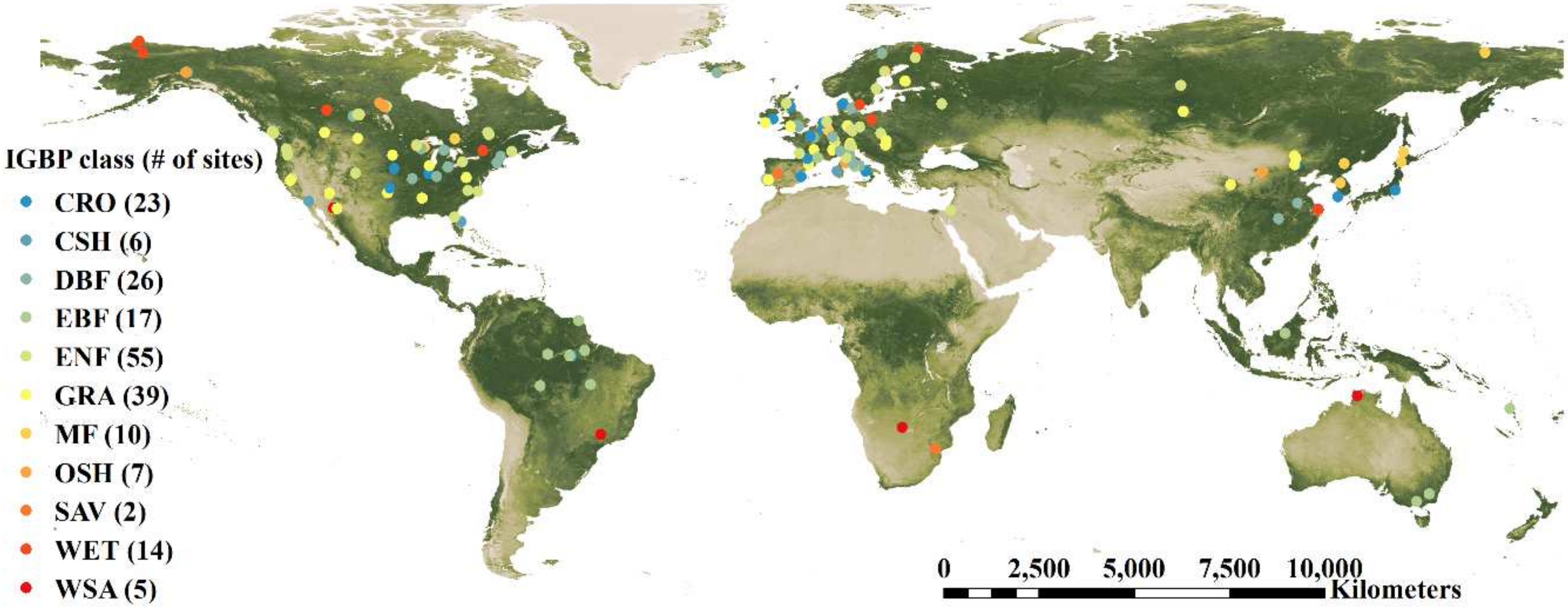


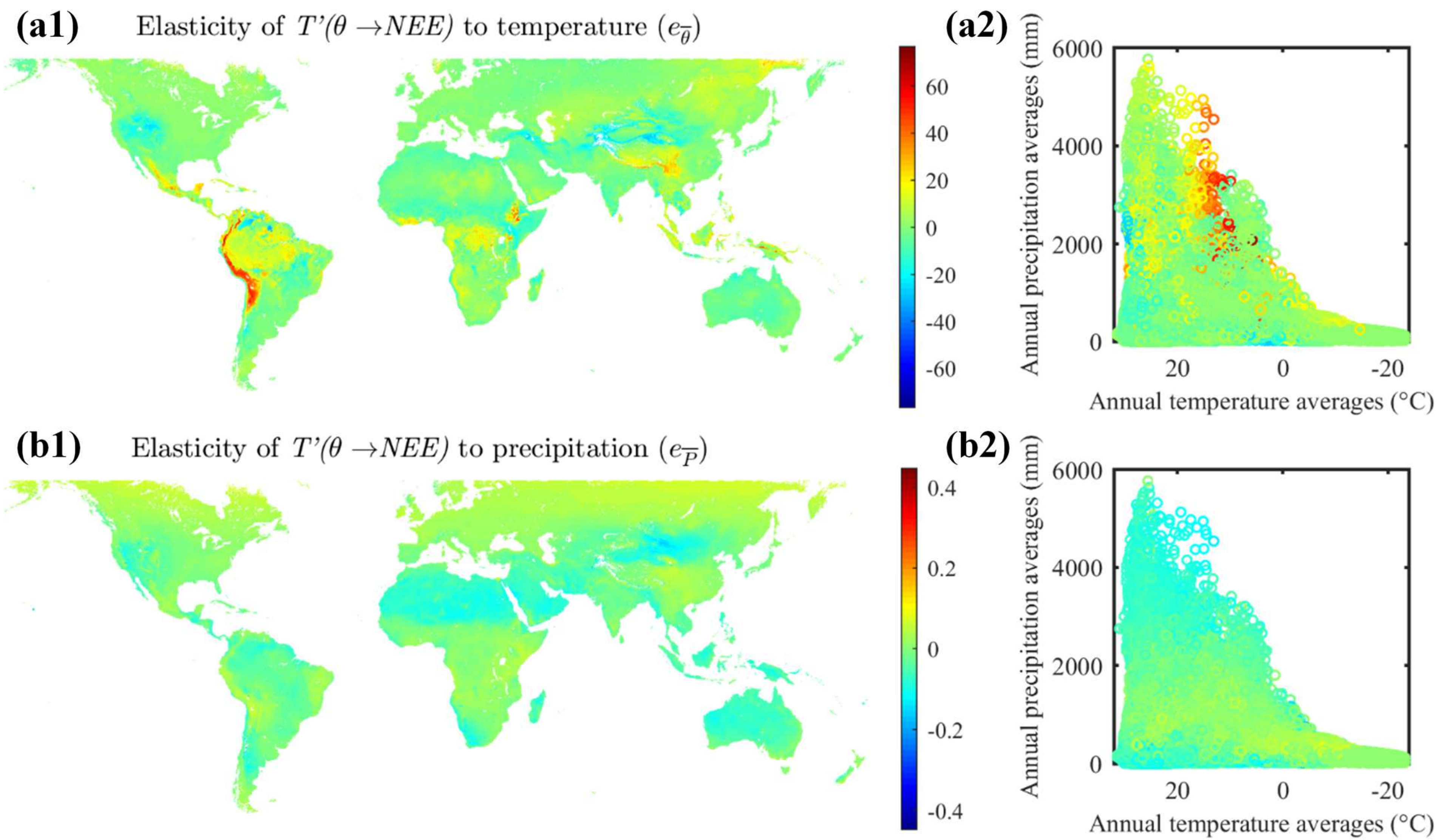
$$T^{`} = \alpha \cdot \bar{\theta}^{\beta_{\bar{\theta}}} \cdot \bar{P}^{\beta_{\bar{P}}} \cdot \bar{R}^{\beta_{\bar{R}}} \cdot \overline{EVI}^{C_{\bar{E}}}$$

$$C_{\bar{E}} = \beta_{\bar{E}} + \gamma_{\bar{\theta}} \ln\bar{\theta} + \gamma_{\bar{P}} \ln\bar{P}$$

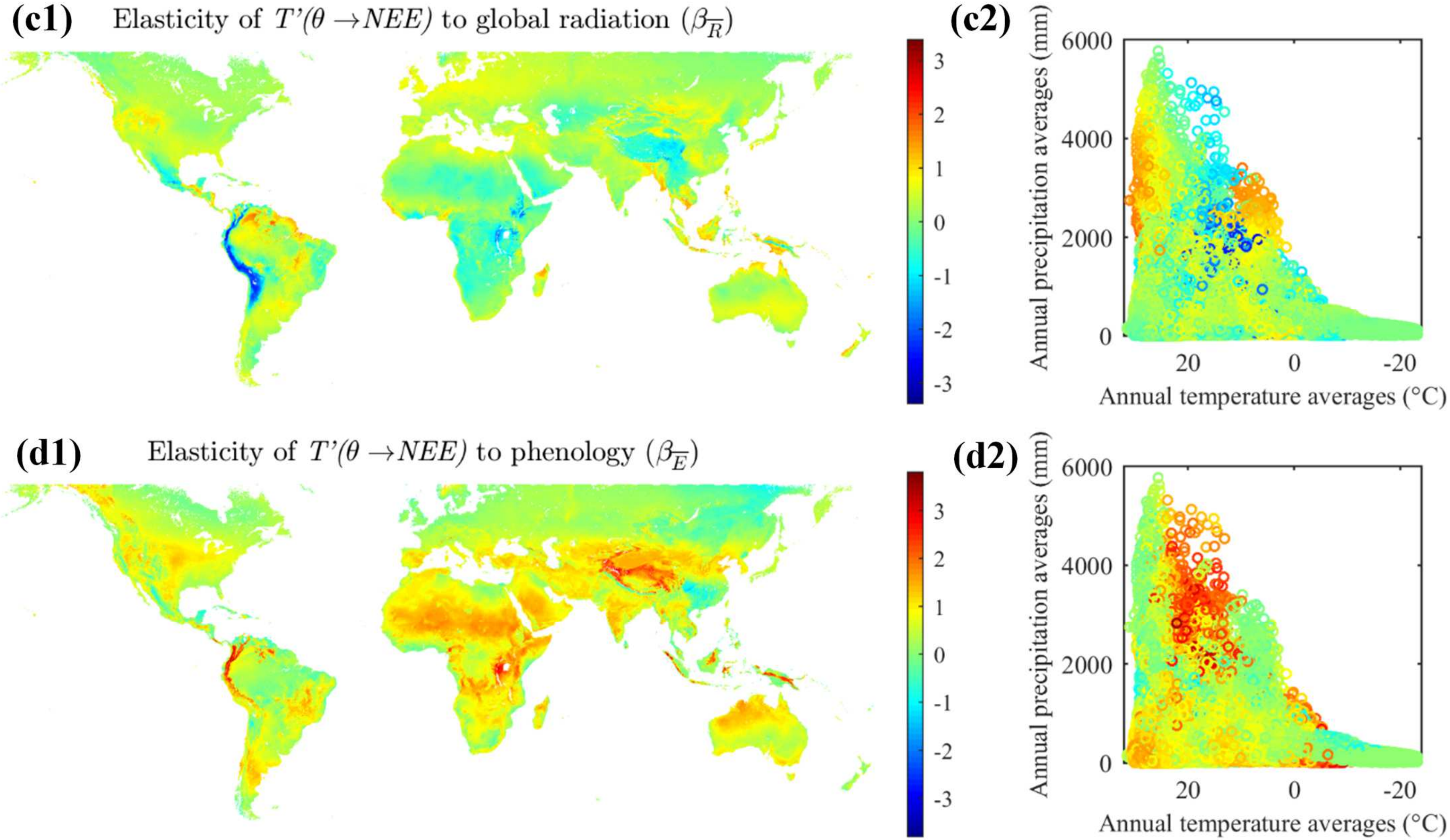
Big Ecological Data: FLUXNET

Thousands of site-years of ‘fast’ dynamics data for diverse ecosystems





Elasticity coefficients are fitted based on OLS for all FLUXNET sites' observed monthly variations in DPN and 'slow' forcing factors, then extrapolated to the world using an ANN based on ecosystem type, geography, and climate



Elasticity coefficients are fitted based on OLS for all FLUXNET sites' observed monthly variations in DPN and 'slow' forcing factors, then extrapolated to the world using an ANN based on ecosystem type, geography, and climate

Model R^2 for Temperature > NEE coupling is better in some ecosystems than others, meaning we know more about the drivers of ecological state change for some ecosystems than others.

IGBP class	Mean	SD	Min	Max	N
OSH	0.875	0.040	0.832	0.912	3
DBF	0.793	0.117	0.471	0.987	23
SAV	0.724	0.169	0.604	0.843	2
EBF	0.716	0.138	0.363	0.935	15
MF	0.693	0.163	0.388	0.918	9
ENF	0.652	0.184	0.214	0.912	41
WET	0.631	0.241	0.282	0.879	7
CRO	0.621	0.207	0.206	0.941	19
GRA	0.599	0.225	0.114	0.910	31
CSH	0.554	0.185	0.390	0.855	6
WSA	0.513	0.262	0.160	0.778	4
Total	0.664	0.196	0.114	0.987	160

International Global Biosphere Programme (IGBP) vegetation class. CRO: croplands; CSH: closed shrublands; DBF: deciduous broadleaf forests; EBF: evergreen broadleaf forests; ENF: evergreen needleleaf forests; GRA: grasslands; MF: mixed forests; OSH: open shrublands; SAV: Savannas; WET: permanent wetlands; WSA: woody Savannas.

Conclusions

- Initial investigation succeeds in explaining changes in ecosystem functional state by studying a simplified subset of the DPN
- Elasticity to seasonal temperatures is by far the strongest, followed by phenophase and radiation, then precipitation
- Large differences in sign and magnitude of elasticity are present, meaning different ecosystems respond differently and are different distances from state transition thresholds
- There are large differences in state transition predictability based in part on ecosystem type. Poor predictability means the observed variation of DPN information content does not match the set of four ‘slow’ forcing factors we tested.
- This work can corroborate & critique ecological process models
- LaThuille-DPN v1.0 database contains complete monthly DPN’s and climate & satellite subsets for all of FLUXNET (LaThuille)
- ProcessNetwork v1.5 is released, with wavelets etc.

Abstract

Under the context of global climate change, it is important to understand the direction and magnitude of different ecosystems respond to climate at the global level. In this study, we applied dynamical process network (DPN) approach combined with eco-climate system sensitivity model and used the global FLUXNET eddy covariance measurements (subdaily net ecosystem exchange of CO2, air temperature, and precipitation) to access eco-climate system sensitivity to climate and biophysical factors at the flux site level. Eco-climate system sensitivity at flux timescales was estimated at the global flux sites and extrapolated to all possible land covers by employing artificial neural network approach. The extrapolation utilizes MODIS phenology and land cover products, the long-term climate GLDAS-2 product, and the GMTED2010 Global Grid elevation dataset. We found that the eco-climate system dynamical process structures are more sensitive to seasonal temperature, than to radiation, phenology, or (lowest sensitivity) precipitation. Interestingly, if global temperature continues rising, the temperature-to-NEE process coupling may increase in tropical rain forest areas while decreasing in tropical desert or Savanna areas. At the same time, phenology showed a positive effect on the temperature-to-NEE process coupling at all pixels, so increased greenness increases the importance of temperature to carbon dynamics and consequently carbon sequestration globally. This work is unique in that it provides a theoretically independent and complex system based means of assessing the sensitivity of global ecosystem processes to climate change, and it can therefore be used to critique or corroborate the findings of process based ecosystem models.