CHINAFLUX第十次培训

通量数据插补与拆分的基本方法

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生态系统网络观测与模拟重点实验室

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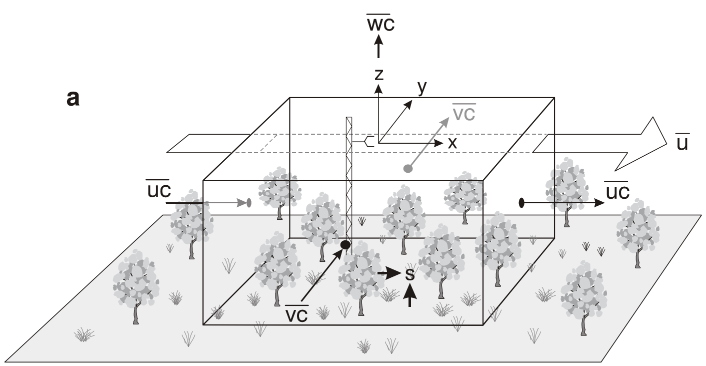
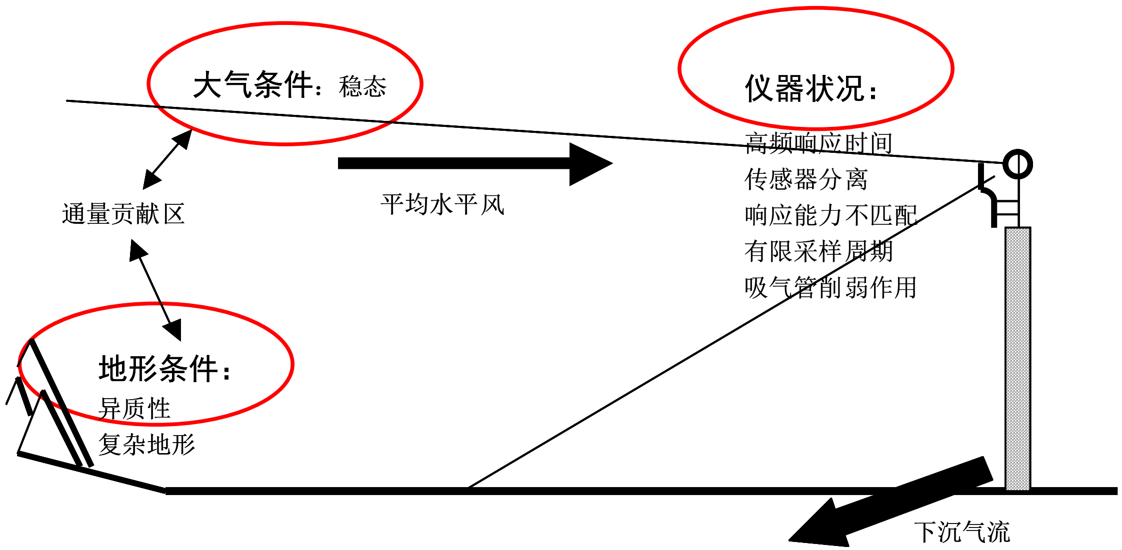
通量观测的主要误差来源

a





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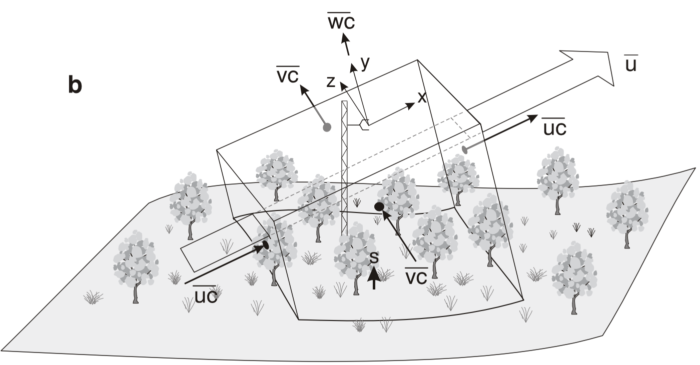


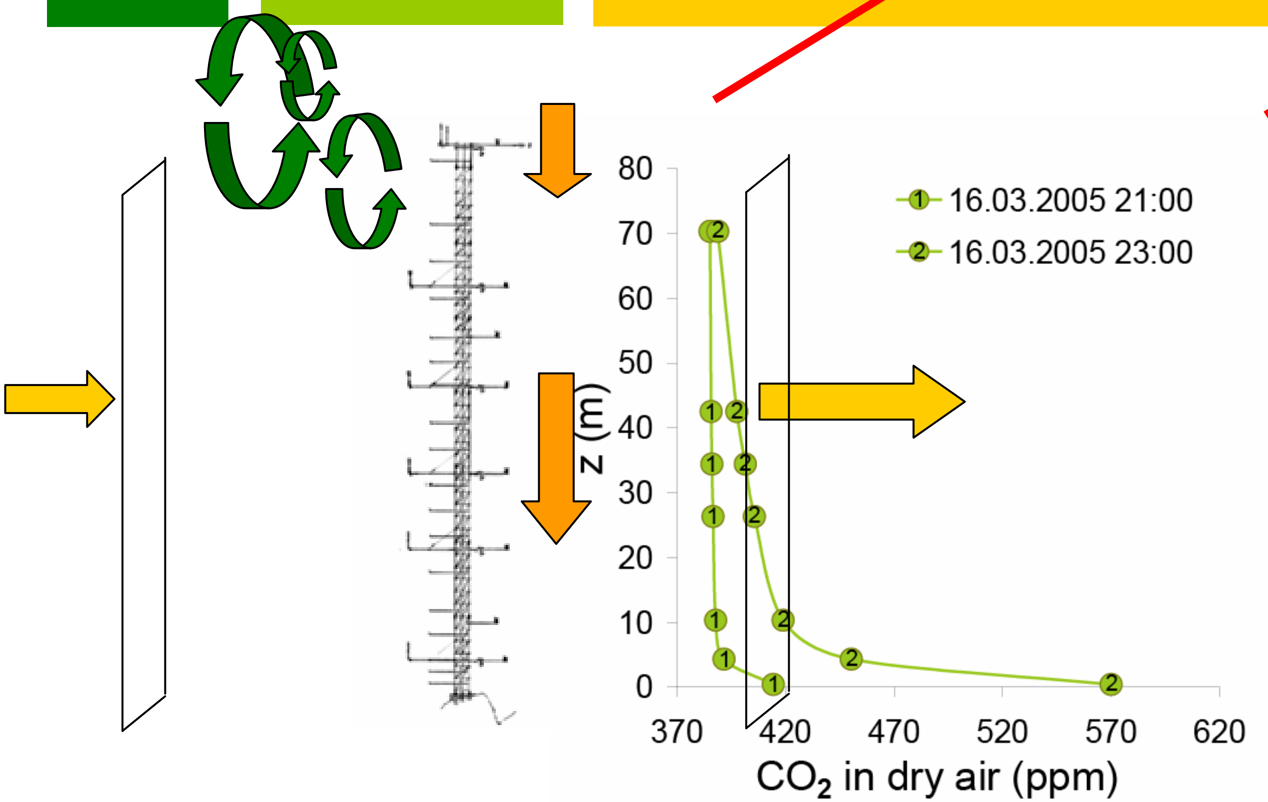
“生态系统尺度”的CO_2和水热通量长期连续的定位观测是从1990年开始的。从微气象学的角度而言，在地势平坦冠层均质且广阔的通量观测站所获得的碳水通量测定数据是最值得信赖的。

现实中陆地生态系统主要分布在复杂的地形条件下，这种条件下难以完全满足涡度相关技术的基本假设条件，仍然存在很多技术问题与仪器/大气/地形条件有关.

地形（下垫面）、 仪器、 大气条件

通量观测的理论公式

$$\mathrm{NEE} = \overline{w'c'}(h_r) + \int_0^{h_r} \frac{\partial \overline{c}(z)}{\partial t} dz + \cancel{\int_0^{h_r} \left(\overline{u}(z) \frac{\partial \overline{c}(z)}{\partial x} + \overline{v}(z) \frac{\partial \overline{c}(z)}{\partial y} \right) dz} + \cancel{\int_0^{h_r} \overline{w}(z) \frac{\partial \overline{c}(z)}{\partial z} dz}$$



通量观测数据的质量控制

（1）原始数据分析

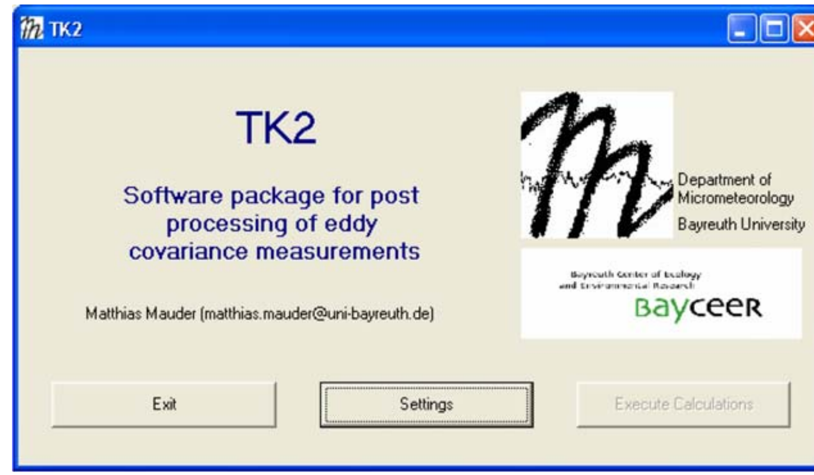
（2）湍流的稳态测试

（3）大气湍流统计特性分析

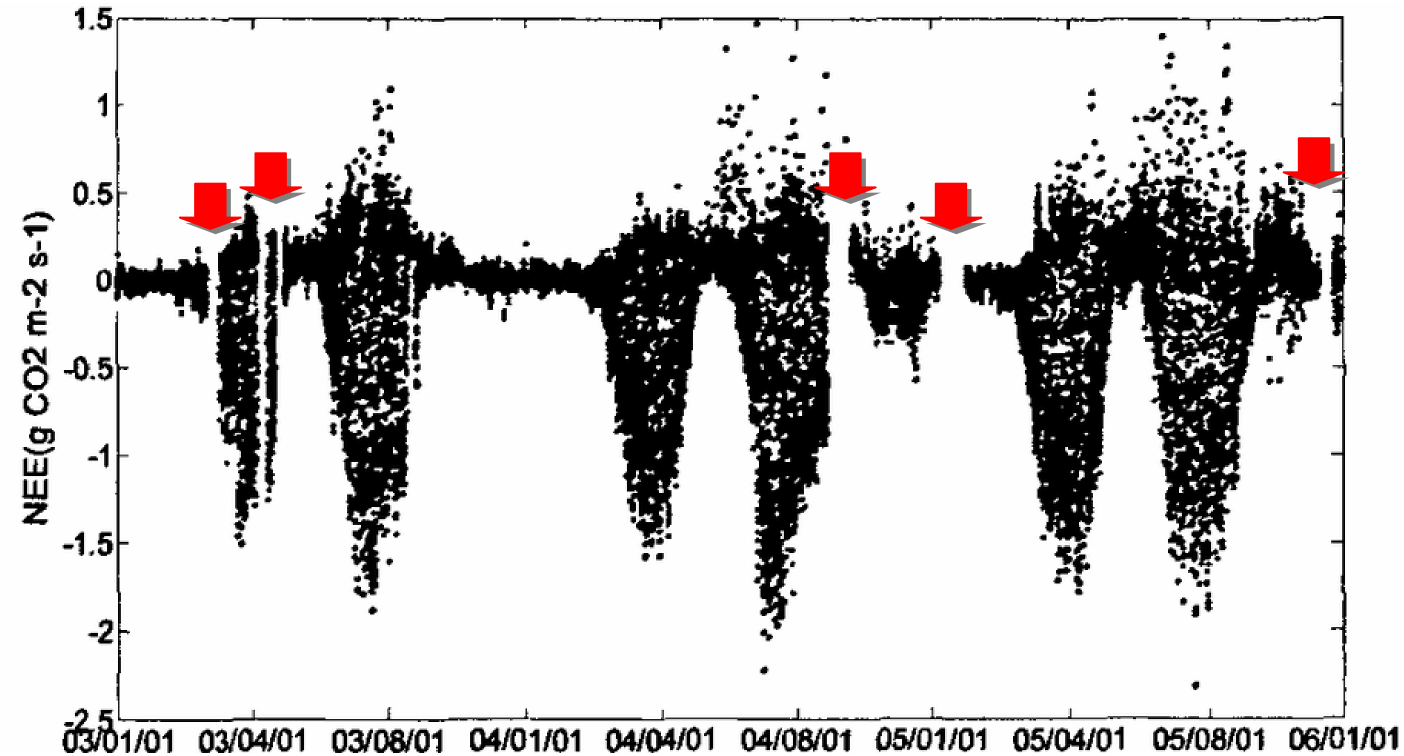
（4）能量平衡闭合评价

……

数据质控与处理软件



- 自行编写



- 如何形成完整的观测数据？

李春等，2009

通量缺失数据的插补和拆分策略

1. 通量数据插补与拆分的前提与必要性

2. 通量数据缺失原因和常用插补方法

3. 通量拆分常用方法

插补与拆分的前提

- 通量数据已经进行必要的校正和质量控制
  - 坐标旋转
  - 谱校正
  - WPL校正
  - 储存项校正
  - 稳态测试
  - 夜间数据处理
  - … …

插补与拆分的必要性

- 从实际观测角度而言，无法期待通量观测能够提供不间断的观测数据；
- 基于涡度相关技术在生态系统尺度上的独特性，希望基于EC的观测计算不同时间尺度，特别是年尺度的碳源汇、水分平衡能力；
- 模型开发与应用人员需要完整的通量数据及其组分以发展和检验模型。

通量缺失数据的插补和拆分策略

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通量数据的缺失原因

因站点而异的数据缺失原因

- 观测系统故障、标定和维护
- 原始数据中的“野点”剔除
- 特定风向来源观测数据的剔除
- 外界环境对开路系统光路的干扰，如降水和水气凝结
- 农事操作、人为管理活动
- … …

共性的数据缺失原因

- 低湍流交换，如夜间U*阈值的筛选
- 质量评价和筛选 (i.e., Foken and Wichura, 1996)
- 储存项校正（CO_2数据缺失）

常用数据插补方法

基本原则

- 尽可能利用各类观测数据
- 尽可能少的利用经验假设关系
- 尽可能减少估算偏差

Workshop on Gap Filling Comparison September 18-20, 2006, Jena, Germany

Organizer: Antje Moffat

目的

- 综合分析不同的数据查补和组分拆分方法
- 对不同方法的结果进行统计和评价
- 估算不同方法得到的日、月、季节和年尺度的误差
- 提出欧洲通量网标准的数据查补和拆分方案

Gap Filling Technique	Member	Abbrev.
:::::::::: Data-based non-linear regressions ::::::::::		
Non-linear Regression (AQRTa model)	Askoo Noormets	NLR_A
Non-linear Regression (Eyring, Michaelis-Menten (ER,GEP))	Ankur Desai	NLR_EM
Non-linear Regression (2nd order Fourier, Michaelis-Menten) OLS = Ordinary-Least-Squares, AD = Absolute-Deviation	Andrew Richardson	NLR_FM
Non-linear Regression (Lloyd+Taylor, Michaelis-Menten)	Eva Falge	NLR_LM
Non-linear Regression (empirical ER, GEP) FCRN - Fluxnet Canada Research Network	Alan Barr	NLR_FCRN
:::::::::: Artificial neural networks ::::::::::		
Artificial Neural Networks	Dario Papale	ANN1
Artificial Neural Networks	Antje Moffat	ANN2
Baysian Regularized ANN with time series filtering	Rob Braswell	BRANN
:::::::::: Other ::::::::::		
Multiple Imputation Method	Dafeng Hui	MIM
Mean Diurnal Variation	Eva Falge	MDV
Look-Up Tables	Eva Falge	LUT
Marginal Distribution Sampling	Markus Reichstein	MDS
Semi-Parametric Light-Use Model	Vanessa Stauch	SPM
Dual Unscented Kalman Filter (Lloyd+Taylor, Michaelis-Menten)	Dave Hollinger, Jeff Gove	UKF_LM
BETHY, a process-based model	Jens Kattge	BETHY

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Agricultural and Forest Meteorology 107 (2001) 43–69

AGRICULTURAL AND FOREST METEOROLOGY

www.elsevier.com/locate/agrformet

Gap filling strategies for defensible annual sums of net ecosystem exchange☆

Eva Falge[a,r,*], Dennis Baldocchi[a], Richard Olson[b], Peter Anthoni[c], Marc Aubinet[d], Christian Bernhofer[e], George Burba[f], Reinhart Ceulemans[g], Robert Clement[h], Han Dolman[i], André Granier
Niels-Otto Jensen[l], Ga
Chun Ta Lai[m], Beverley E.
J. William Munger[p], K
Andrew Suyker[f], John T

Available online at www.sciencedirect.com

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Agricultural and Forest Meteorology 147 (2007) 209–232

AGRICULTURAL AND FOREST METEOROLOGY

www.elsevier.com/locate/agrformet

Comprehensive comparison of gap-filling techniques for eddy covariance net carbon fluxes

Antje M. Moffat[a,*], Dario Papale[b], Markus Reichstein[a], David Y. Hollinger[c],
Andrew D. Rich
Bobby H. Braswell[g]
Jeffrey H. Gove[c], M
Jens Kattge

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Agricultural and Forest Meteorology 121 (2004) 93–111

AGRICULTURAL AND FOREST METEOROLOGY

www.elsevier.com/locate/agrformet

Gap-filling missing data in eddy covariance measurements using multiple imputation (MI) for annual estimations

Dafeng Hui[a,*], Shiqiang W

Biogeosciences, 3, 571–583, 2006
www.biogeosciences.net/3/571/2006/

326次引用

Biogeosciences

Towards a standardized processing of Net Ecosystem Exchange measured with eddy covariance technique: algorithms and uncertainty estimation

D. Papale[1], M. Reichstein[2], M. Aubinet[3], E. Canfora[1], C. Bernhofer[4], W. Kutsch[2], B. Longdoz[5], S. Rambal[6], R. Valentini[1], T. Vesala[7], and D. Yakir[8]

Moffat et al., 2007, AFM

Technique (Variants)	NLR_AM	NLR_EM	NLR_FCRN (STD, MOD)	NLR_FM (AD, OLS)	NLR_LM	UKF_LM	BETHY (12, ALL)
Methodology	Non-linear regression	Non-linear regression	Non-linear regression	Non-linear regression	Non-linear regression	Kalman filter	Terrestrial biosphere model
Description	Classic NLR	Classic NLR	Additional linear regression with time LR(t)	Seasonal ER dependency	Classic NLR	Dual unscented Kalman filter	Biosphere energy-transfer hydrology model
Participant	Asko Noormets	Ankur Desai	Alan Barr	Andrew Richardson	Eva Falge	David Hollinger, Jeff Gove	Jens Kattge
Reference	Noormets et al. (2007)	Desai et al. (2005)	Barr et al. (2004), Fluxnet Canada Res. Network	Hollinger et al. (2004) and Richardson et al. (2006b)	Falge et al. (2001)	Gove and Hollinger (2006)	Knorr and Kattge (2005)
Meteo requirement	×	×	×	×	×	×	×
Process based	×	×	×	×	×	×	×
Auto-correlation						×	
Noise conservation						×	
Data dependencies nighttime	ER = $f(T_a)$; Arrhenius	ER = $f(T_s)$; Eyring	ER = $\alpha(t)f(T_s)$; logistic equation	ER = f(DOY); second-order Fourier	ER = $f(T_s)$; Lloyd–Taylor	ER = $f(T_s)$; Lloyd–Taylor	PPFD, T_a, Rh, SWC, LAI, LE, height of canopy and tower, soil type, texture, and depth
Data dependencies daytime	GPP = f(PPFD); Michaelis-Menten	GPP = f(PPFD); Michaelis-Menten	GPP = $\beta(t)f$(PPFD); Michaelis-Menten	GPP = f(PPFD); Michaelis-Menten	GPP = f(PPFD); Michaelis-Menten	GPP = f(PPFD); Michaelis-Menten	
Time window	Monthly fixed	Moving window (30–60 day adaptive length)	First: annual NLR (T_s, PPFD) Second: 100-valid mov. data points LR(t)	Monthly fixed	Bimonthly fixed	Recursive single steps	Parameterization for ALL: all available data Parameterization for 12: 12 days of data
Remarks	Simultaneous fit of daytime and nighttime data	Additional t-test	STD: linear interpolation of gaps $\leq$4 hhs. MOD: zero intercept and no interpolat	Parameter estimation, AD: absolute deviation, OLS: ordinary least squares	During daytime: 4° C-T_a-classes air temperature classes	Winter dormancy: random walk plus noise	Modeled NEE for whole year
Framework	SAS	IDL	Matlab	SAS	PV-Wave, Fortran	R, Fortran	Fortran, IDL
Runtime (per single run)	Medium (30 s)	Medium (30 s)	Fast (5 s)	Medium (30 s)	Fast (5 s)	Fast (5 s)	Very slow (2–6 h)
Ease of implementation	Medium	Medium	Medium	Medium	Medium	Complex	Complex
Performance hh daytime	Good	Good	Good	Good	Good	Medium	Good
Performance hh nighttime	Low	Low	Low	Low	Low	Low	Low
Performance daily daytime	Good	Good	Good	Good	Good	Good	Good
Performance daily nighttime	Medium	Medium	Medium	Medium	Medium	Low	Medium
Reliability of annual sum	Medium	Low (negative bias)	Medium	Medium	Good (above average)	Low (long gaps)	Low (site bias)

Moffat et al., 2007, AFM

Technique (Variants)	ANN_BR	ANN_PS	ANN_S	LUT	MDS	SPM	MDV	MIM
Methodology	Artificial neural network	Artificial neural network	Artificial neural network	Look-up table	Moving "LUT"	3D continuous "LUT"	Diurnal interpolation	Monte Carlo technique
Description	Bayesian network regularization	Date pre-sampling and network smoothing	Standard	Fixed look-up table	Marginal distribution sampling	Semi-parametric model	Mean diurnal variation	Multiple imputation method
Participant	Rob Braswell	Dario Papale	Antje Moffat	Eva Falge	Markus Reichstein	Vanessa Stauch	Eva Falge	Dafeng Hui
Reference	Braswell et al. (2005)	Papale and Valentini (2003)	Moffat (in preparation)	Falge et al. (2001)	Reichstein et al. (2005)	Stauch and Jarvis (2006)	Falge et al. (2001)	Hui et al. (2004)
Meteo requirement	×	×	×	×	(×)	×		(×)
Process based								
Auto-correlation	(×)	(×)	(×)	×	×	×	×	
Noise conservation					(×)	(×)	(×)	×
Data dependencies nighttime	All available meteo data	T_a, T_s, Rh, SWC plus fuzzies for DOY	All available meteo data plus fuzzies for HOD and DOY	35 T_s classes	Look-up of similar meteo conditions of margin: $R_g < 50$ W m^{-2}, $T_a < 2.5$ °C, VPD < 5.0 h Pa	Cubic spline interpolation of semi-parametric model $f(R_g, T, t)$	f(NEE, t)	All available meteo plus NEE
Data dependencies daytime		R_g, T_a, Rh, SWC, sin, cos		23 PPFD classes and 35 T_a classes				Same as above
Time window	Full year	Pre-sampling into equal subsets: 28 periods with three daytime slots	Full year	Bimonthly	Sliding window $\pm n \times 7$ days, with $n \geq 1$ to find data within margin	Continuous	Sliding window of daytime: ±14-days, nighttime: ±7-days	Full year
Remarks	Time series filtering	Network smoothing by sampling of networks and training data, averaging over 6 best			Algorithm varies for incomplete meteo, see reference			Introduces uncertainties to emulate natural variability
Framework	Matlab	Matlab	C++	PV-Wave, Fortran	PV-Wave	Matlab	PV-Wave, Fortran	SAS
Runtime (per single run)	Medium (1 min)	Slow (10 min)	Medium (1 min)	Medium (30 s)	Fast (1–5 s)	Very slow (2 days)	Fast (1 s)	Fast (1–2 s)
Ease of implementation	Complex	Complex	Complex	Easy	Easy	Complex	Easy	Easy
Performance hh daytime	Good (above average)	Good (above average)	Good (above average)	Good	Good	Good	Medium	Medium
Performance hh nighttime	Low	Low (above average)	Low	Low	Low	Low	Low	Low
Performance daily daytime	Very good	Very good	Very good	Good	Very good	Good	Medium	Medium
Performance daily nighttime	Medium	Medium (above average)	Medium	Medium	Medium	Medium	Medium	Low
Reliability of annual sum	Good (above average)	Good	Low (outliers)	Good	Good	Good	Medium	Low (outliers)

常用数据插补方法

经验方法:

- 简单方法：线性内插、变量关系、相邻替代资料
- 平均日变化：Mean Diurnal Variation
- 非线性回归法：Nonlinear Regressions (PPFD, Tair, etc.,)
- 查表法：Look Up Tables (PPFD, Tair, VPD, etc.,)
- 边际分布采样法：Marginal Distribution Sampling (PPFD, Tair, VPD)

统计方法:

- 人工神经网络：Artificial Neural Networks (ANN)
- 多重分配：Multiple Imputation (MI)
- 状态依赖参数估计法：State Dependent Parameter Estimation
- …

简单方法: 线性内插

- 只适合于小的GAP (1-3个连续缺失数据)
- 特别适合于短期缺失的常规气象要素的查补 (Tair, rH, 等)

缺点:

- 只能插补很短时间的缺失数据

08:30	09:00	09:30	10:00	10:30	11:00
19.58	19.59			19.52	19.57

对于缺失数据:

09:30: 19.59+(19.52-19.59)/3=19.57

10:00: 19.57+(19.52-19.59)/3=19.54

or

19.59+2*(19.52-19.59)/3=19.54

简单方法: 变量关系（气象数据）

- 利用气象变量之间的相互关系互相插补

  PPFD and Rg

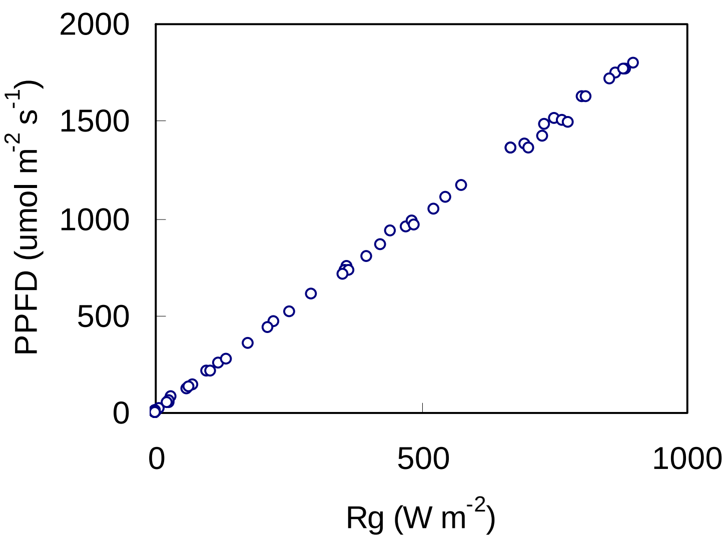
  VPD, Tair, rH

  u*, momentum

- 例如，PPFD缺测时候，可以利用有效的 PPFD和Rg观测数据建立线性关系，再利用建立的关系插补缺失的PPFD数据。

缺点:

- 变量关系只适用于特定的变量
- 每个站点的变量关系是不同。



简单方法: 邻近观测（气象数据）

- 通量观测中没有安装常规观测系统；
- 常规气象系统长时间数据缺失；
- 邻近观测站具备常规气象观测，并且地形和环境条件基本相似；

缺点:

- 即使是地理位置上靠近通量观测塔，但由于小气候的空间变异很大，特别是在地形复杂的山区，气象要素会发生一定的变化。

经验方法:平均日变化

Mean Diurnal Variation, MDV

- 先确定时间窗口，通常的时间窗口是4-15天，一般选择7和14天的比较多；
- 将时间窗口内同一时刻的观测数据进行平均，得到一组平均日变化数据；
- 平均日变化中的缺失数据利用线性内插进行插补；
- 利用对应时刻的平均日变化数据插补缺失数据。

平均日变化的类型

- 总体上，平均日变化有两种不同的形式：固定窗口“independent” window和滑动窗口“gliding” window；
- 对于固定窗口而言，每个窗口的起始时间是固定的，之后计算平均日变化，用以插补时间窗口内的缺失数据。
- 对于滑动窗口，每个时间窗口按固定时间长度向前滑动，计算平均日变化，然后用以缺失数据的插补。

MDV计算方法

DOY	…	8	9	10	11	12	13	14	15	16	17	18	19	20	21	…
00:30	---	19.33		22.75	24.18	22.15	20.46		19.91	18.42		21.21	24.09		23.35	---
01:00	---	19.49	21.64	22.33	23.58	22.25	19.91	20.02	18.42	18.42	19.36	21.26	24.45	24.02	23.28	---
01:30	---	19.6	21.46	22.08	23.41	22.21	19.45	20.55	18.47	17.67	19.16	21.23	24.62	23.71	23.26	---
02:00	---	19.55		22.14	23.37	22.15	19.53		17.64		19.37	21.21	24.48		22.99	---
02:30	---	19.57	21.38	22.43	23.25	22.05	19.63	19.15	17.53	17.23	19	21.24	24.42	22.84	22.75	---
03:00	---	19.53	21.42	22.7	23.33	21.84	19.91	18.54	17.01	17.39	18.85	21.68	24.37	22.55	23.02	---
03:30	---	19.5	21.35	22.39	23.43	21.39	19.84	18.81	16.58	17.1	18.92	21.78	24.21	22.43	22.73	---
04:00	---	19.44	21.31	22.25	23.3	20.97	19.46	18.57	17.11	17.15	18.89	21.21	24.12	22.42	22.53	---
04:30	---	19.42	21.39	22.04	23.03	20.24	19.35	18.47	17.4	17.02	18.92	20.54	23.73	22.12	22.35	---
05:00	---	19.42	21.29	21.64	23.03	19.45	19.27	18.35	16.79	16.64	18.71	20.75	23.38	22.21	22.09	---
05:30	---	19.45	21.08	21.26	22.7	19.05	19.24	17.94	16.91	16.69	18.48	20.22	23.08	22.13	21.62	---
06:00	---	19.56	21.04	21.44	22.58	18.45	19.22	17.85								---
06:30	---	19.86	21.17	21.33	22.61	17.99	19.37	17.75	16.01	16.7	18.06	20.21	23.04	21.4	21.55	---
07:00	---	19.96	21.4	21.09	22.6	17.87	19.01	17.59	15.89	16.4	17.75	20.07	22.75	21.43	21.42	---
07:30	---	19.86	21.53	21.09	22.6	17.71	18.94	17.21	15.88	16.36	17.66	20.11	22.71	21.31	21.64	---
08:00	---	20.09	21.68	21.53	22.68	17.55	18.73	17.99	16.58	16.93	17.99	20.14	22.64	21.51	21.96	---

平均日变化的特点

优点:

- 适合于常规气象数据也缺失的情况;
- 总体而言，在原始数据缺失较少的情况下，MDV方法可以提供较好的估算和插补。

缺点:

- 如果进行计算的日变化的数据是在特定条件下的观测数据，因此，被插补数据可能不是现实情况下的真实反映;
- 没有利用一定的生理生态方程进行约束;
- 适合于短时间的GAP (<14 days).

经验方法: 非线性回归

Nonlinear Regression

- 利用预先设定的方程对白天和夜间数据分开进行处理和插补;
- 插补的时间窗口通常是2个月或者4个季节。
- 考虑到方程拟合效果和插补偏差，一般对于白天数据时间窗口可以缩短，夜间要长一些。

夜间缺失数据

- 利用不同的经验方程：Lloyd & Taylor, Arrhenius, or Van’t Hoff equations (4 or 6 period/yr)

Lloyd & Taylor

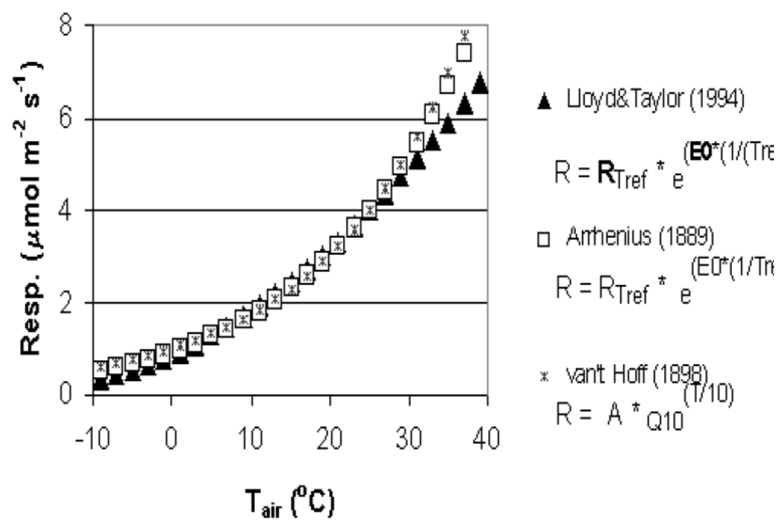
$$NEE_{night} = Reco_{night} = R_{ref} \cdot e^{E_0\left(\frac{1}{T_{ref}-T_0} - \frac{1}{T_K - T_0}\right)}$$

Arrhenius

$$NEE_{night} = Reco_{night} = R_{ref} \cdot e^{\frac{E_A}{R}\left(\frac{1}{T_{ref}} - \frac{1}{T_K}\right)}$$

Van’t Hoff

$$NEE_{night} = Reco_{night} = A \cdot e^{(B \cdot T)}$$

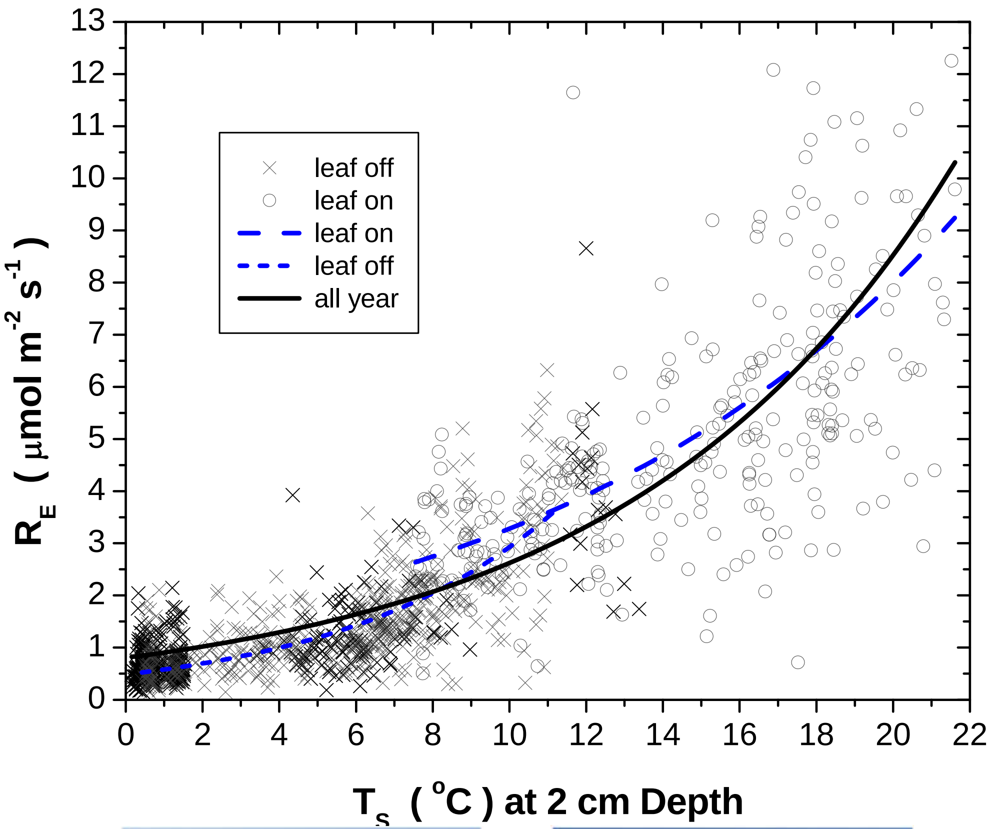


参考温度下的生态系统呼吸

生态系统呼吸的温度敏感性

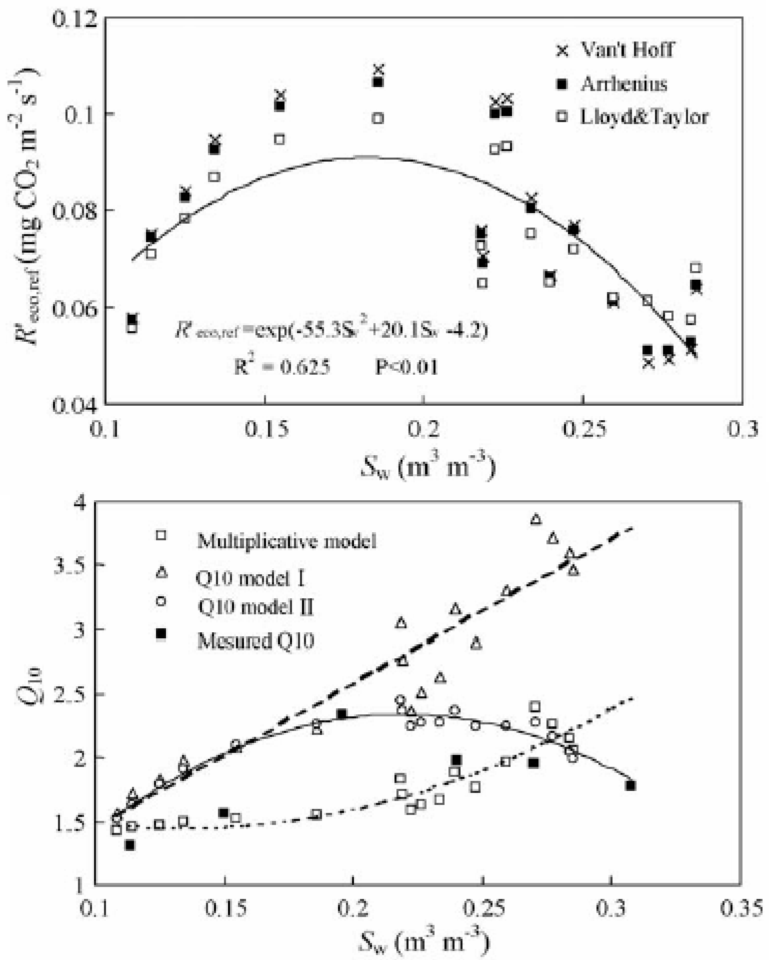
夜间观测数据与土壤温度

(measurements from UMBS, Schmid et al., 2003)



- 一般认为，生态系统呼吸（夜间观测数据）和空气温度/土壤表层温度存在显著的指数关系；
- 生态系统呼吸随着温度的升高而指数上升；
- 数据越离散表明受到其它环境要素的作用越强。
- 呼吸模型：$R_E = a \cdot \exp(b \cdot T_S)$

土壤水分对夜间观测数据与温度关系的影响



水分对生态系统呼吸的影响:

- 土壤干旱会降低根系和土壤微生物的活性，导致呼吸排放速率降低；
- 土壤脱水可导致根周活性降低；
- 但同时，土壤水分过大可能会减少土壤中的氧气浓度，导致微生物活性受到抑制。

Q10 Model,

$$R_{eco} = R_{eco,refs}\, e^{\ln(Q_{10})(T_K - T_{ref})/10}$$

$$Q_{10} = a - bT_K + cS_w + dS_w^2$$

Wen et al., 2006 AFM

白天缺失数据

- 利用不同形式的光响应方程 (包括线性linear 、抛物线parabolic和双曲线hyperbolic等)；
- Michaelis–Menten or Misterlich functions.

$$NEE_{day} = \frac{a' \cdot Q_{PPFD} \cdot F_{GPP,sat}}{F_{GPP,sat} + a' \cdot Q_{PPFD}} - F_{RE,day}$$

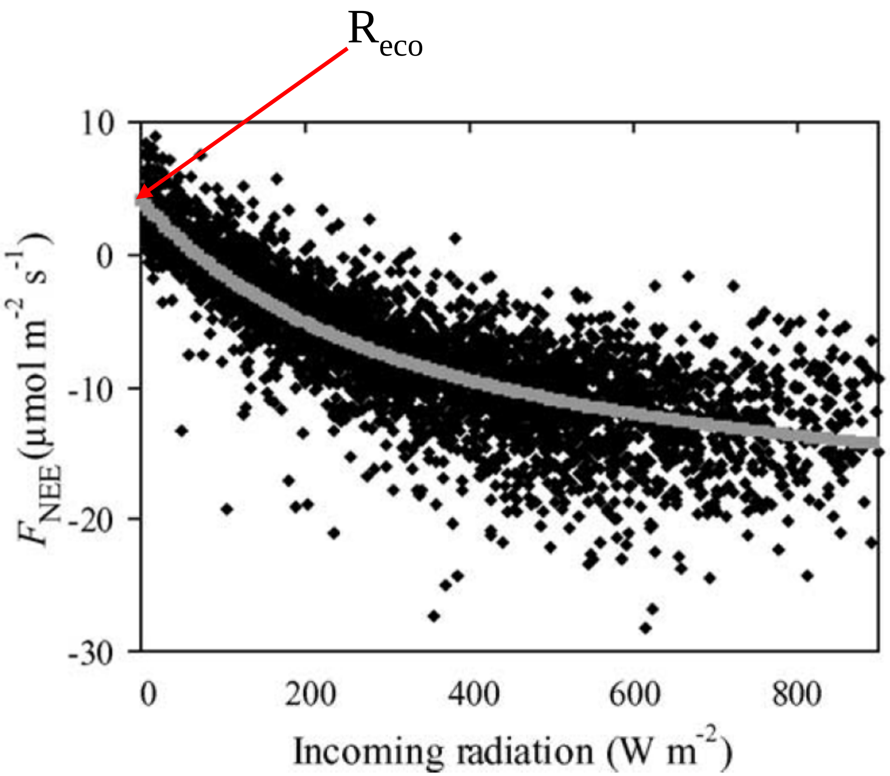
Michaelis-Menten

或

$$NEE_{day} = F_{GPP,opt}\left(1 - e^{\frac{a' \cdot Q_{PPFD}}{F_{GPP,opt}}}\right) - F_{RE,day}$$

Misterlich

白天观测数据与光合有效辐射

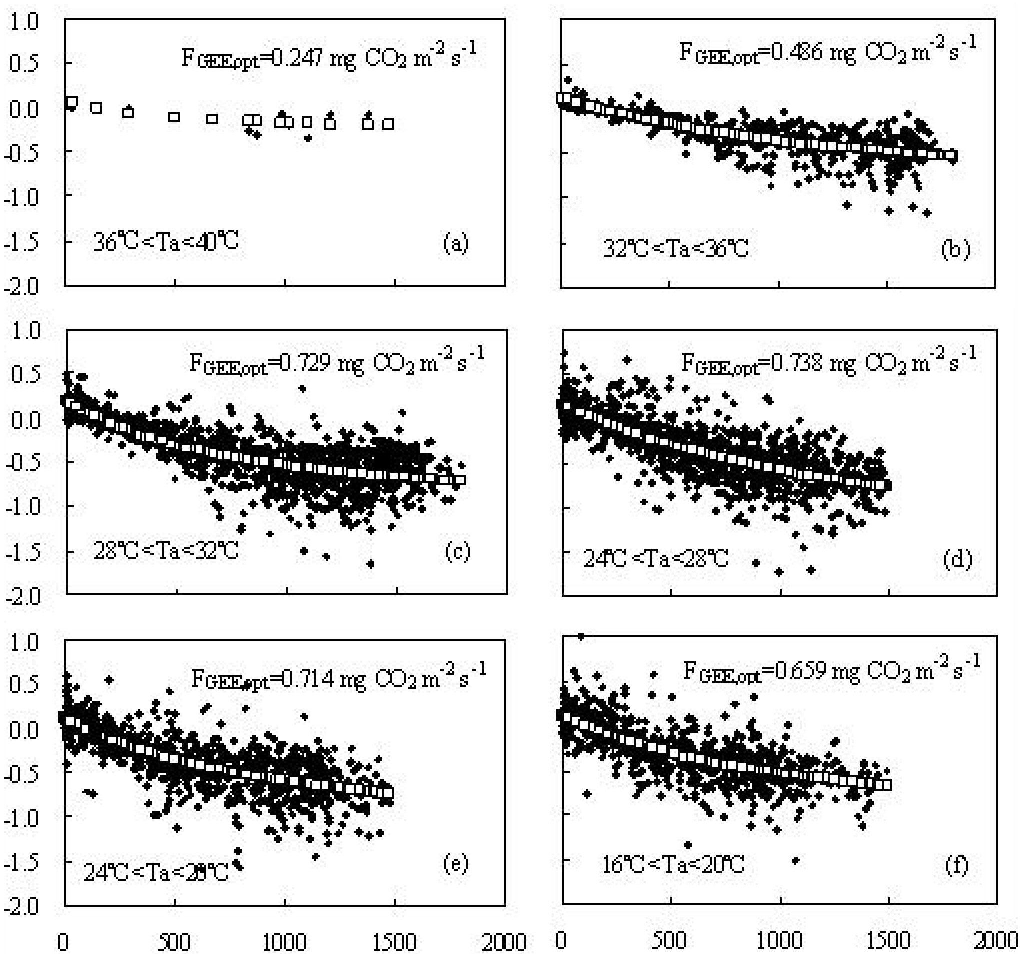


Carrara et al., 2004, AFM

- 一般情况下，生长季期间，生态系统光合作用（此处指白天的通量）会随着PPFD的增强而升高；但是当光强达到一定程度之后，光合作用趋于饱和。
- 利用生长季内的白天数据，在不同的时间窗口中建立上述关系，之后插补缺失数据。
- 与呼吸相同，数据越离散，表明通量越受到其它环境要素的作用。

$$NEE = \frac{\alpha \cdot A_{C,Sat} \cdot PPFD}{A_{C,Sat} + \alpha \cdot PPFD} - \mathrm{Re}$$

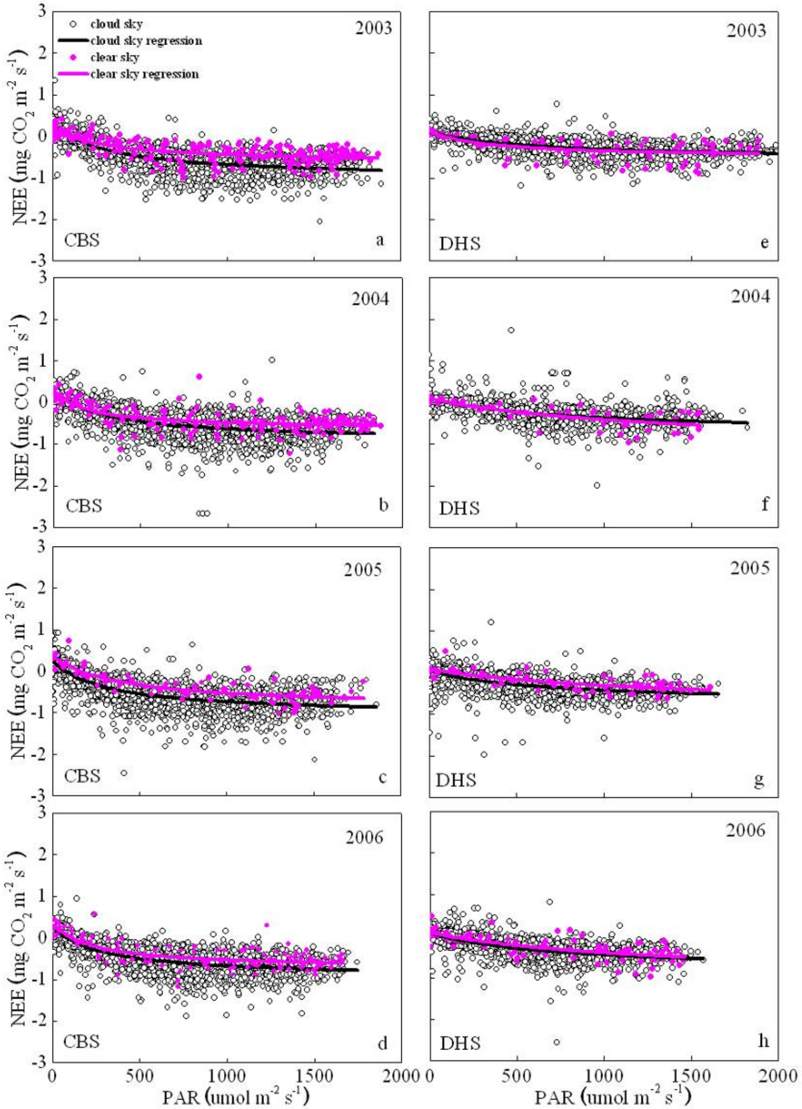
气象要素对白天观测数据与光合有效辐射关系的影响



实际应用时，可以考虑按不同的环境条件进行分组，然后分别建立关系进行插补:

如按温度进行分组，每4度作为一组，分别建立方程(Liu et al., 2006).

多云天气的影响



- 晴天和多云天气的差异（Zhang et al., 2009）

非线性回归的特点

优点:

- 非线性回归的方法是建立在对通量主控因子的理解基础之上，因此，这种方法可以很好的捕捉主要环境要素变化对通量的影响，从而比较准确的插补缺失数据；

缺点:

- 预先确定的方程并不总是有效，比如说在干旱条件下水分有效性就成为主要的控制因子；
- 预先设定的方程也往往是很多过程模型的重要部分，因此，利用非线性回归插补数据对模型进行验证时可能有一定的风险；
- 如果常规气象要素同时缺失，该方法将无法应用。
- 适合于短时间的数据GAP。

经验插补方法: 查表法

- 基于2个月或1个季度分别建立数据检索表;
- 在每个检索表内，分别按光强和气温对检索表内的数据分组：即six (or four) seasonal periods×23PPFD-classes×35 Ta-classes;
- PPFD按每100 μmol m^{-2} s^{-1}分级，从 0 到 2200 共分23级别，其中PPFD=0是单独一级;
- 气温按 2℃ 分级，从 −19℃ to 49℃ (根据站点具体情况确定)分为35级;
- 然后分别计算每个级别有效数据的平均值，如果某个级别没有，则进行线性内插补充完整。
- 对检索表检索，查询相似条件下的数据插补缺失数据。

Fagle et al., 2001 AFM

查表法的特点

Look-up Tables

- 基于有效数据建立数据检索表；
- 根据主要环境因子进行检索，查找相似环境条件下的有效数据；
- 将查找到的有效数据进行平均，插补缺失数据，如 利用气温和PPFD检索碳通量数据。

缺点:

- 用于检索的环境要素必须完整；
- 数据可能会比较离散，因为尽管环境条件相同，也可能由于风向和地形影响使得查找到的数据差别较大，由此导致插补的不确定性也较大。

经验插补方法: 边际分布采样法

Marginal Distribution Sampling (MDS)

- 假设:

❖ NEE = NEE(Rg, Tair, VPD, time) + ε

❖ NEE (Rg, Tair, VPD, time) ≅ NEE(Rg+ΔRg, Tair+ΔTair, VPD+ΔVPD, time+Δtime)

❖ Δtime越小、环境约束变量越多，则插补效果越好

(Reichstein et al. 2005 GCB)

边际分布采样法的基本步骤

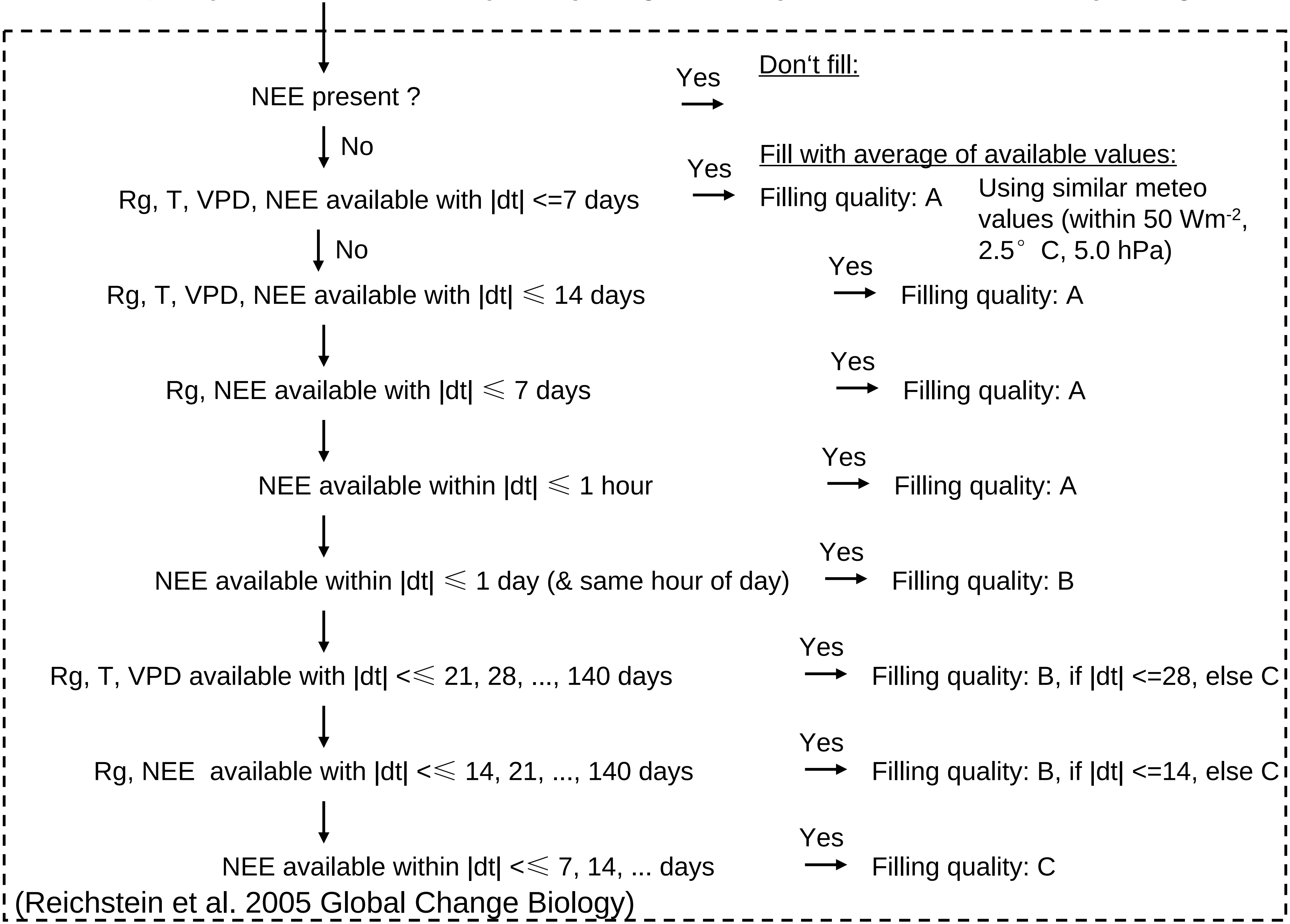
- **步骤1：** 以缺失数据为中心，计算前后14天内具有相似气象条件的有效观测数据的平均值；
- 相似气象条件：总辐射(Rg)、气温(T_{air})和VPD的变化幅度分别不超过50 Wm^{-2}, 2.5℃和5.0 hPa；
- 如果能够找到相似气象要素下的有效数据以插补缺失数据，则插补质量标记为“A”；
- **步骤2：** 如果没有插补，则将时间窗口延长到前后28天，插补质量仍然标记为“A”。
- **步骤3：** 如果还没有插补，则将时间窗口缩短到前后14天，相似气象条件仅仅用总辐射(Rg)表示，插补质量仍然标记为“A”。
- **步骤4：** 如果还没有插补，则将时间窗口缩短到前后2个小时，以该时段内有效数据的平均值插补，插补质量仍然标记为“A”。

边际分布采样法的基本步骤

- **步骤5：** 如果仍未插补缺失数据，则以缺失数据为中心，计算前后2天同时刻有效观测数据的平均值，插补质量标记为“B”；
- **步骤6：** 如果没有插补，计算前后42天内具有相似气象条件（总辐射、气温和VPD）的有效观测数据的平均值，插补质量仍然标记为“B”。
- **步骤7：** 如果还没有插补，则将时间窗口缩短到前后28天，相似气象条件仅仅用总辐射(Rg)表示，插补质量仍然标记为“B”。
- **步骤8：** 如果还没有插补，则以缺失数据为中心，计算前后14天同时刻有效观测数据的平均值，插补质量标记为“C”；
- **步骤9：** 如果还没有插补，重复步骤5-9，并且每次延长时间窗口14天，插补质量均标记为“C”。

Reichstein et al. Gap Filling Method

Quality-controlled half-hourly data (storage, ustar,...)



边际分布采样法的特点

- 基本的技术途径和查表法相似 (Falge et al., 2001);
- 将MDV和Look-up Tables两种方法进行了综合。
- 区别在于:
  - 动态的平均窗口 (as small as possible ➔ better exploitation of temporal autocorrelation)
  - 滑动的“ look-up table (➔ value to be filled always in the center of the class)

数据插补效果的评价

- 采用人为GAP的方式，对比分析观测数据与插补数据；

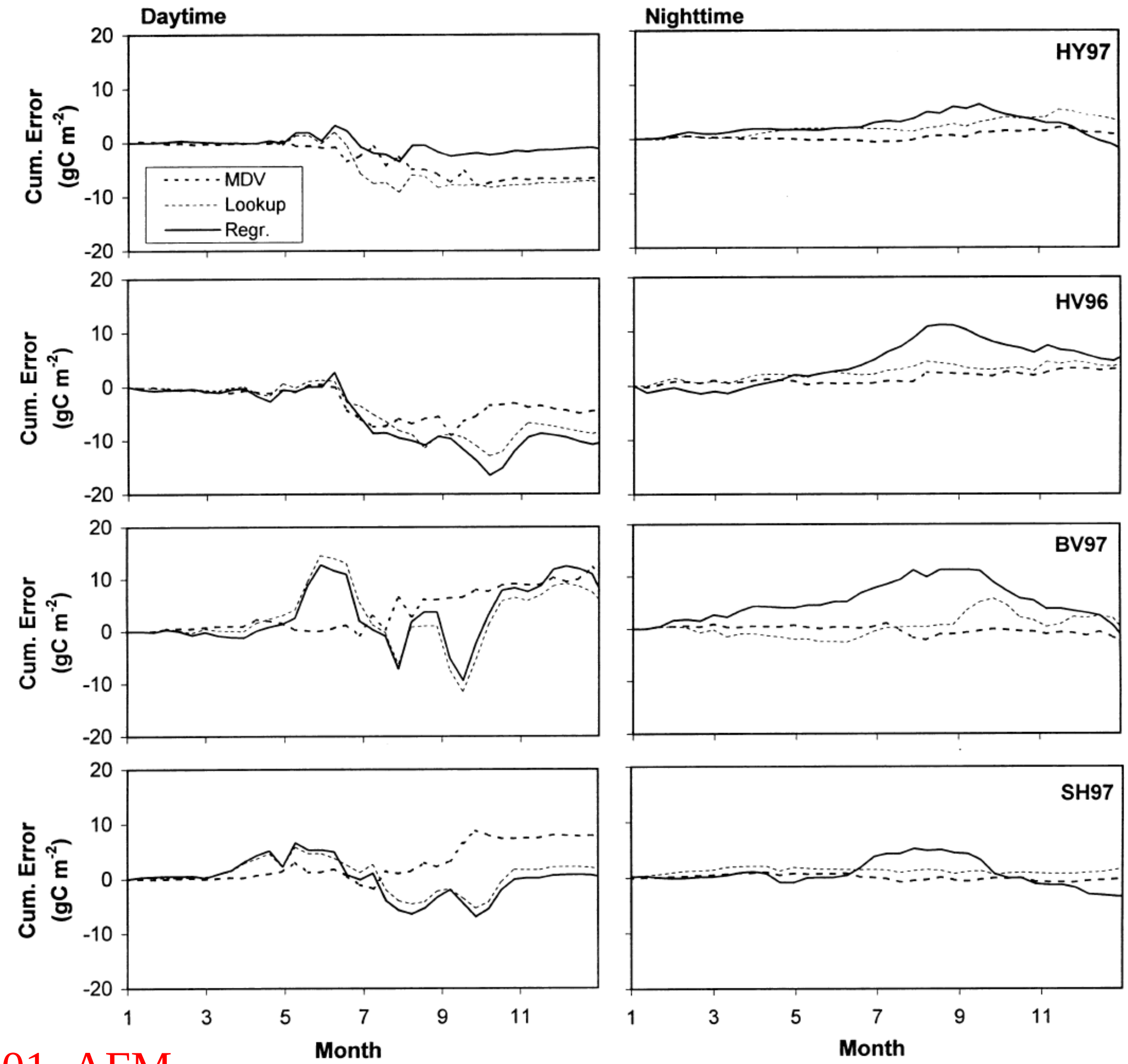
Moffat et al., 2007, AFM

Description of the five artificial gap length scenarios (‘v’, ‘s’, ‘m’, ‘l’, ‘x’) with 10 random permutations each (‘0’ to ‘9’)

Header	Gap length	Amount of half-hours	Count of gaps	Count of total hhs
v0, . . ., v9	Very short	1 (0.5 h)	1752	1752
s0, . . ., s9	Short	8 (4 h)	219	1752
m0, . . ., m9	Medium	64 (~1.5 days)	27	1728
l0, . . ., l9	Long	576 (12 full days)	3	1728
x0, . . ., x9	Mix of the above	400 v, 50 s, 6 m and 1 l gap	457	~1760

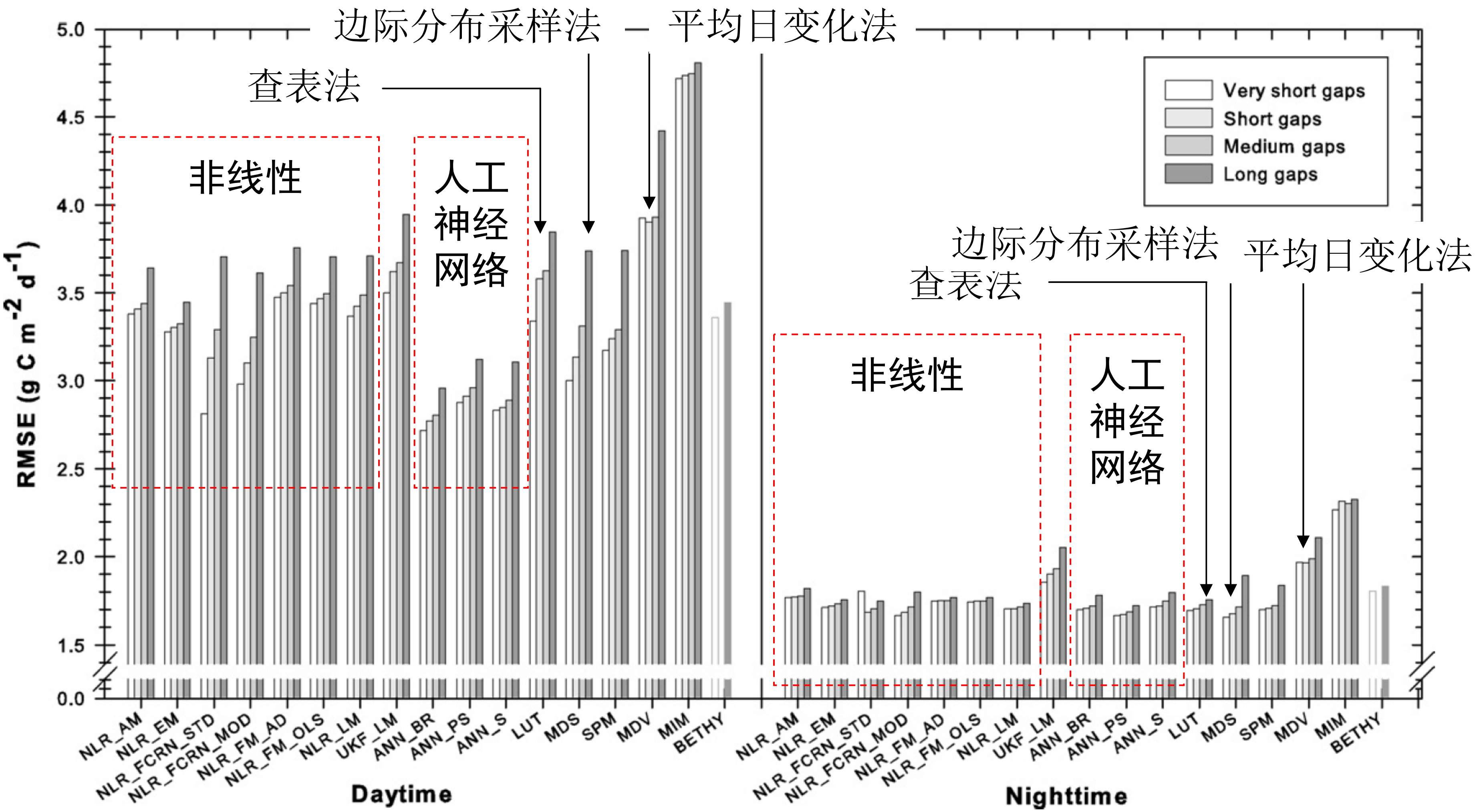
- 采用Monte-Carlo或Bootstrap方法，对原数据集进行反复取样（如1000次以上）形成新数据集，然后重新插补并统计变异范围；

不同插补方法的比较

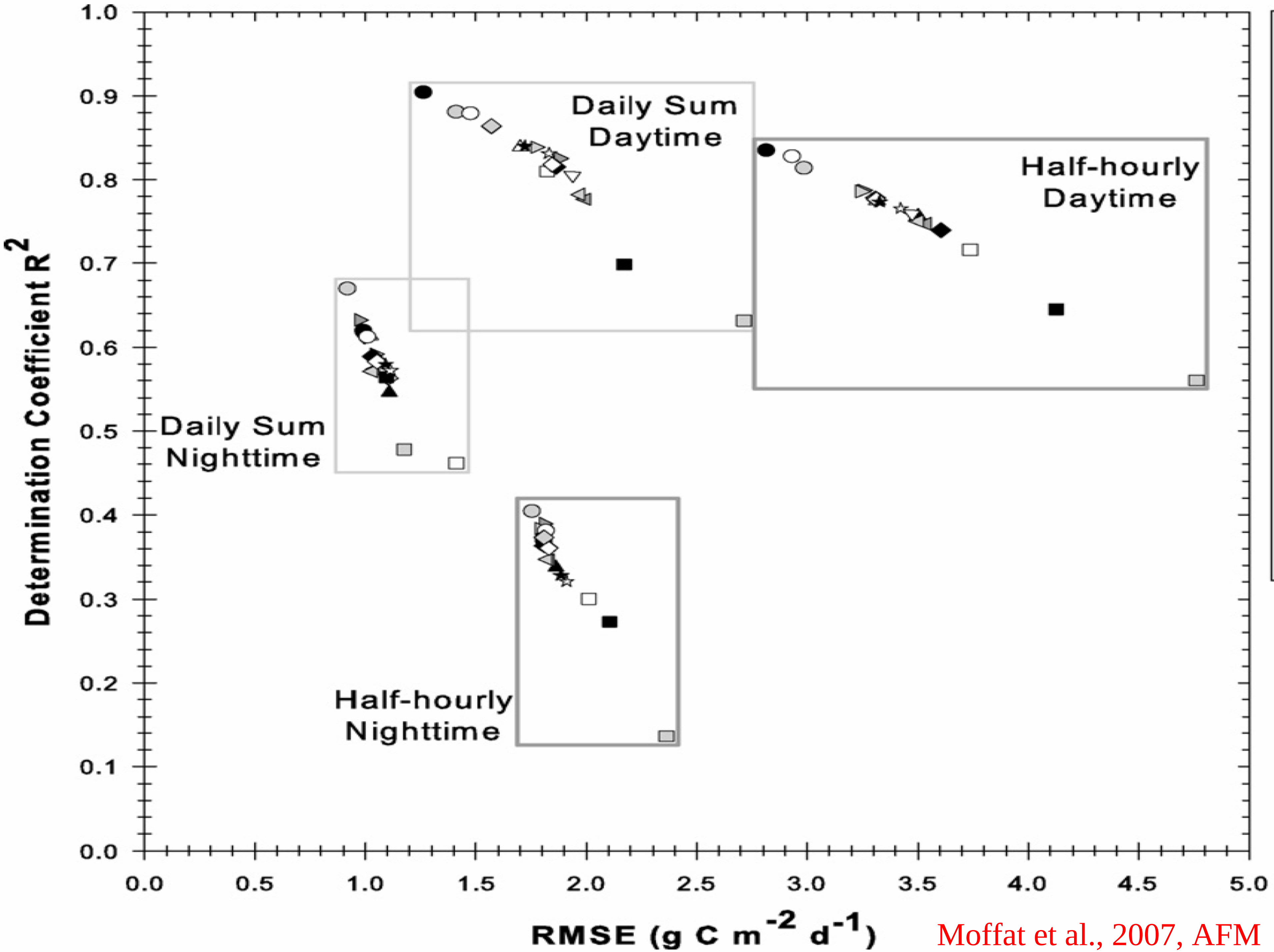


Falge et al., 2001, AFM

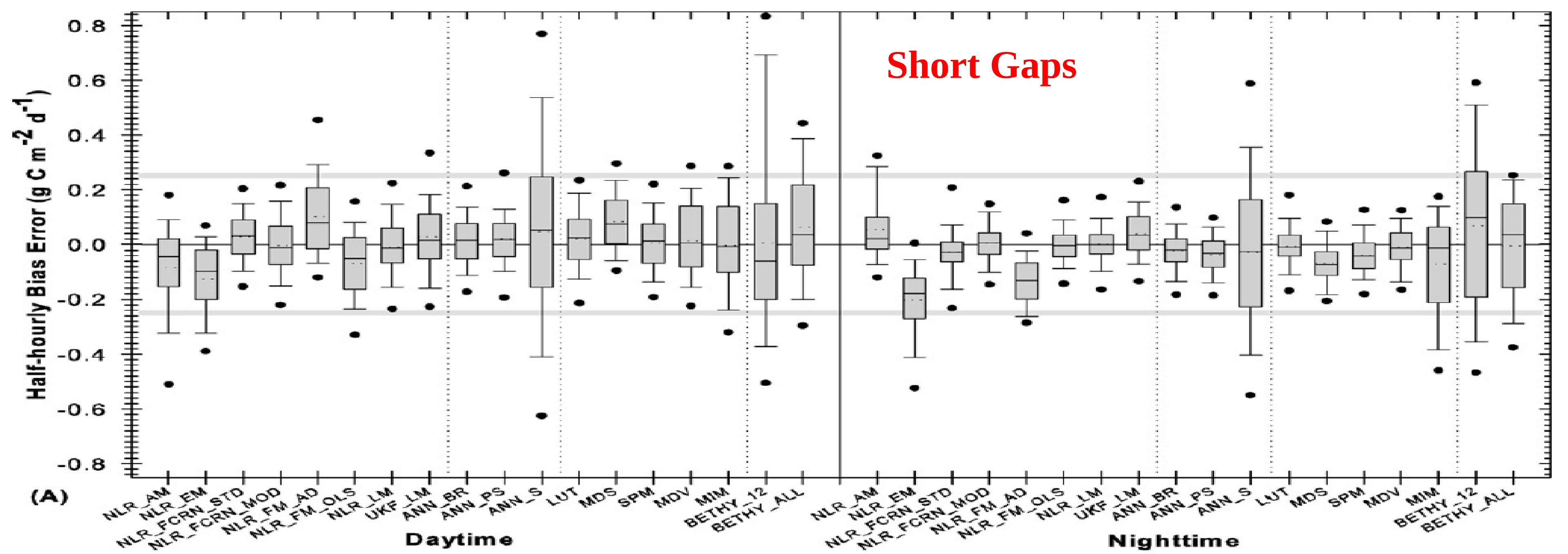
不同插补方法的比较



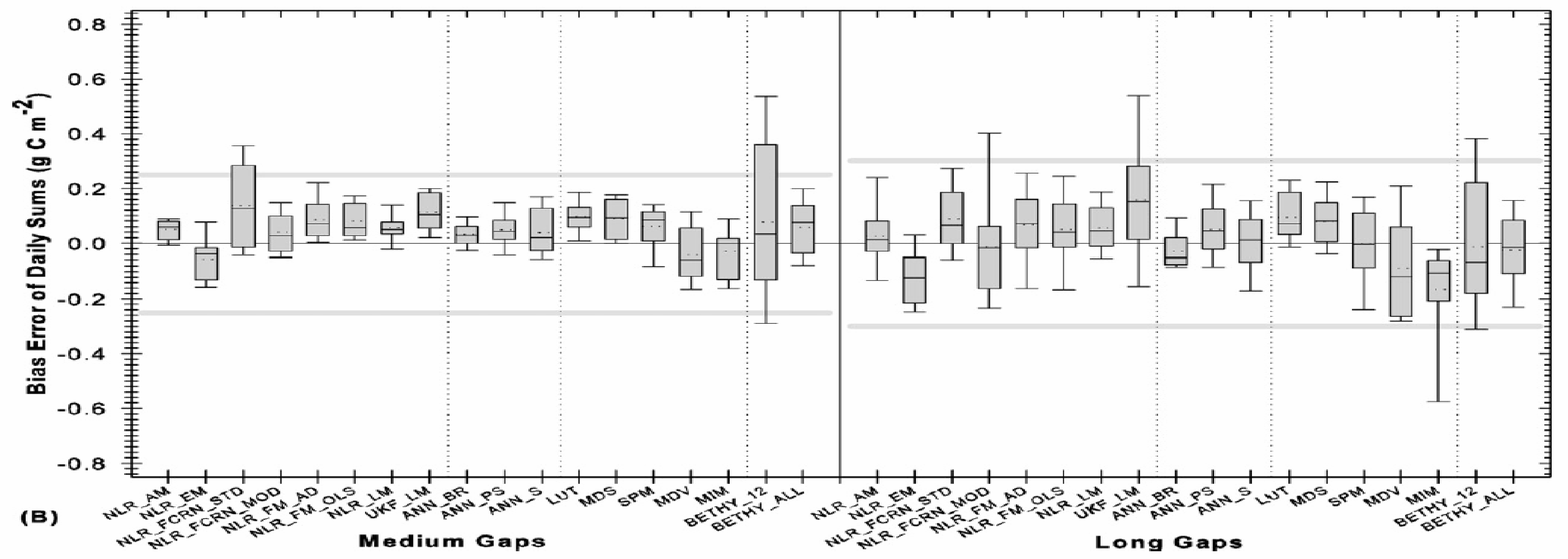
Moffat et al., 2007, AFM



Moffat et al., 2007, AFM



Moffat et al., 2007, AFM



插补策略小结

- 如果没有气象要素的观测，则只能选用平均日变化（MDV）方法进行缺失数据的插补；
- 多数的研究是利用查表法（Look-up tables）或者非线性回归法（Nonlinear regression method）插补缺失数据，因为这些方法有效的约束了插补数据，或者体现了通量对环境要素的响应特征（如：PPFD和温度）；
- 边际分布采样法（Marginal Distribution Sampling）有效结合了MDV和Look-Up Table两种方法，并且已经被 EUROFLUX 接受为标准的插补方法。
- 数据缺失越少，特别是缺失窗口越小，其插补的可信度越高。因此，需要加强对通量观测系统的维护，以尽量保障数据的连续性。

通量缺失数据的插补和拆分策略

1. 通量数据插补与拆分的前提与必要性

2. 通量数据缺失原因和常用插补方法

3. 通量拆分常用方法

常用的碳通量拆分方法

NEP=GEP-Reco

- 碳通量拆分一般是先估算生态系统呼吸Reco，然后计算得到生态系统光合GEP。
- 根据Reco的估算方法，常用的碳通量拆分方法可以分为两大类：
- **（1）利用夜间观测数据估算：通过拟合夜间有效数据和温度等环境因子响应方程的参数，基于方程推算白天生态系统呼吸**
  - 夜间观测数据质量
  - 尺度外推
- **（2）利用白天观测数据估算：通过拟合白天有效数据和PPFD响应方程中的R_{eco}参数，建立R_{eco}和温度等环境因子的关系，推算生态系统呼吸**
  - 光响应方程的形式
  - VPD和气温的影响

夜间方式

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Eva Falge[a,r,*], Dennis Baldocchi[a], Richard Olson[b], Peter Anthoni[c], Marc Aubinet[d], Christian Bernhofer[e], George Burba[f], Reinhart Ceulemans[g], Robert Clement[h], Han Dolman[i], André Granier[j], Patrick Gross[j], Thomas Grünwald[e], David Hollinger[k], Niels-Otto Jensen[l], Gabriel Katul[m], Petri Keronen[n], Andrew Kowalski[g], Chun Ta Lai[m], Beverley E. Law[c], Tilden Meyers[o], John Moncrieff[h], Eddy Moors[i], J. William Munger[p], Kim Pilegaard[l], Üllar Rannik[n], Corinna Rebmann[q], Andrew Suyker[f], John Tenhunen[r], Kevin Tu[s], Shashi Verma[f], Timo Vesala[n], Kell Wilson[o], Steve Wofsy[p]

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Eva Falge[a,*], Dennis Baldocchi[b], John Tenhunen[a], Marc Aubinet[c], Peter Bakwin[d], Paul Berbigier[e], Christian Bernhofer[f], George Burba[g], Robert Clement[h], Kenneth J. Davis[i], Jan A. Elbers[j], Allen H. Goldstein[b], Achim Grelle[k], André Granier[l], Jón Guðmundsson[m], David Hollinger[n], Andrew S. Kowalski[o], Gabriel Katul[p], Beverly E. Law[q], Yadvinder Malhi[h], Tilden Meyers[r], Russell K. Monson[s], J. William Munger[t], Walt Oechel[u], Kyaw Tha Paw U[v], Kim Pilegaard[w], Üllar Rannik[x], Corinna Rebmann[y], Andrew Suyker[g], Riccardo Valentini[z], Kell Wilson[r], Steve Wofsy[t]

$$F_{\mathrm{RE,night}} = A\,\mathrm{e}^{(BT)}$$

$$F_{\mathrm{RE,night}} = F_{\mathrm{RE,Tref}}\,\mathrm{e}^{[E_0(1/(T_{\mathrm{ref}}-T_0))-(1/(T_{\mathrm{K}}-T_0))]}$$

白天方式

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T.G. Gilmanov[e,*], J.F. Soussana[e], L. Aires[a], V. Allard[e], C. Ammann[i], M. Balzarolo[p], Z. Barcza[q], C. Bernhofer[o], C.L. Campbell[c], A. Cernusca[l], A. Cescatti[k], J. Clifton-Brown[b], B.O.M. Dirks[f], S. Dore[p], W. Eugster[j], J. Fuhrer[i], C. Gimeno[d], T. Gruenwald[o], L. Haszpra[q], A. Hensen[f,g], A. Ibrom[n], A.F.G. Jacobs[h], M.B. Jones[b], G. Lanigan[b], T. Laurila[s], A. Lohila[t], G.Manca[k], B. Marcolla[k], Z. Nagy[r], K. Pilegaard[m], K. Pinter[r], C. Pio[a], A. Raschi[m], N. Rogiers[u], M.J. Sanz[d], P. Stefani[m], M. Sutton[c], Z. Tuba[r,s], R. Valentini[p], M.L. Williams[b], G. Wohlfahrt[l]

Global Change Biology
Global Change Biology (2010) **16**, 187–208, doi: 10.1111/j.1365-2486.2009.02041.x

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Separation of net ecosystem exchange into assimilation and respiration using a light response curve approach: critical issues and global evaluation

GITTA LASSLOP*, MARKUS REICHSTEIN*, DARIO PAPALE†, ANDREW D. RICHARDSON‡, ALMUT ARNETH§, ALAN BARR¶, PAUL STOY|| and GEORG WOHLFAHRT**

Global Change Biology (2005) **11**, 1424–1439, doi: 10.1111/j.1365-2486.2005.001002.x

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On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm

MARKUS REICHSTEIN*†, EVA FALGE‡, DENNIS BALDOCCHI§, DARIO PAPALE*, MARC AUBINET¶, PAUL BERBIGIER‖, CHRISTIAN BERNHOFER**, NINA BUCHMANN††‡‡, TAGIR GILMANOV§§, ANDRÉ GRANIER¶¶, THOMAS GRÜNWALD**, KATKA HAVRÁNKOVÁ‖‖, HANNU ILVESNIEMI***, DALIBOR JANOUS‖‖, ALEXANDER KNOHL††§, TUOMAS LAURILA†††, ANNALEA LOHILA†††, DENIS LOUSTAU‡‡‡, GIORGIO MATTEUCCI§§§, TILDEN MEYERS¶¶¶, FRANCO MIGLIETTA‖‖‖, JEAN-MARC OURCIVAL****, JUKKA PUMPANEN††††, SERGE RAMBAL****, EYAL ROTENBERG‡‡‡‡, MARIA SANZ§§§§, JOHN TENHUNEN¶¶¶¶, GÜNTHER SEUFERT§§§, FRANCESCO VACCARI‖‖‖‖, TIMO VESALA‖‖‖‖‖, DAN YAKIR‡‡‡‡ and RICCARDO VALENTINI*

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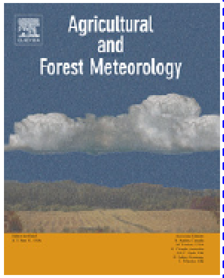
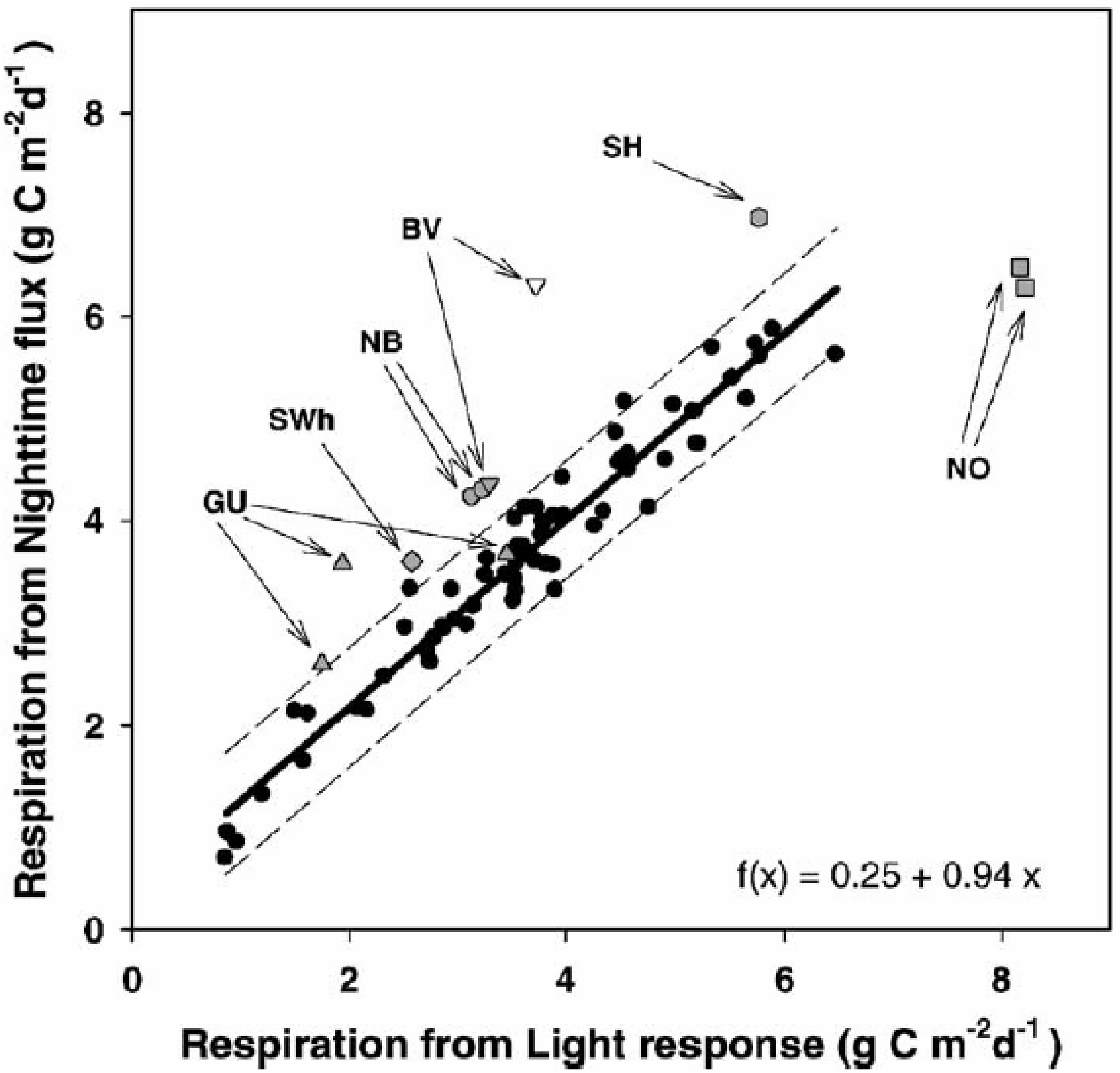


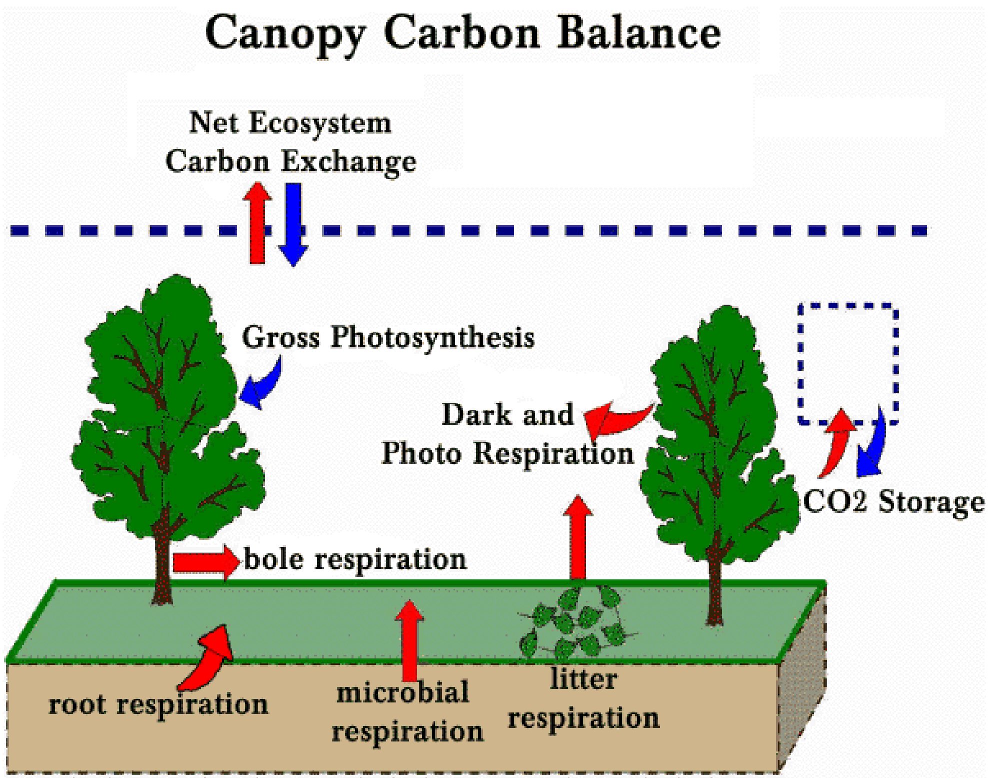
Cross-site evaluation of eddy covariance GPP and RE decomposition techniques

Ankur R. Desai[a,1,*], *Andrew D. Richardson*[b], *Antje M. Moffat*[c], *Jens Kattge*[c], *David Y. Hollinger*[d], *Alan Barr*[e], *Eva Falge*[f], *Asko Noormets*[g], *Dario Papale*[h], *Markus Reichstein*[c], *Vanessa J. Stauch*[i]



Falge et al., 2002, AFM

通量拆分的含义



- 从实际观测角度而言，通量观测只能提供净交换信息；
- NEP=-NEE=GEP-Reco
- 生态系统光合碳吸收（生态系统初级生产力，GEP）和生态系统呼吸碳排放（生态系统呼吸，Reco）决定了NEE的大小和变化；
- 但是通量观测无法直接提供GEP和Reco的信息；
- 在分析和解释NEE的变化和环境响应时，需要分析GEP和Reco的贡献

Table 1 Classification of currently available statistical flux-partitioning algorithms of eddy covariance net CO_2 flux data

Algorithm	Advantages	Disadvantages
(A) Using only night-time data	Flux data is directly used, i.e. direct estimation of R_{eco}	Filtering of bad night-time data necessary, extrapolation to daytime necessary; near and above the polar circle few or no night-time data in summer, respectively
1. Representation of R_{eco} by one single function of temperature (Hollinger *et al*., 1994)	Simplicity	Only applicable where no other factors than temperature influence R_{eco} significantly, not generic
2. Representation of R_{eco} by one single function of temperature and other factors (Reichstein *et al*., 2002a; Rambal *et al*., 2003)	Simplicity, not only temperature as factor considered; allows for seasonally varying temperature sensitivity	Results in selection of site specific factors that determine R_{eco}, not generic
3. Representation of R_{eco} by temporally varying functions of temperature (R_{ref} varying, one single temperature sensitivity derived from annual data set (Falge *et al*., 2002a; Law *et al*., 2002)	Accounts for temporally varying respiration rates at reference temperature, caused by any factor	Long-term temperature sensitivity from annual data set may not reflect short-term response, introduction of systematic error when extrapolating to daytime
4. Representation of R_{eco} by temporally varying functions of temperature (R_{ref}varying, one single temperature sensitivity derived from short-term data set (this study)	Accounts for temporally varying respiration rates at reference temperature, caused by any factor, 'correct' temperature response avoids introduction of systematic error when extrapolating to daytime	Seasonally varying temperature sensitivity not accounted for
5. Representation of R_{eco} by temporally varying functions of temperature (both R_{ref} and temperature sensitivity varying) (this study)	Accounts for temporally varying respiration rates at reference temperature, caused by any factor, seasonally varying temperature sensitivity is accounted for	Often noisiness of eddy covariance data does not allow derivation of temperature sensitivity for large periods of the year with statistical significance, i.e. limited practical applicability
(B) R_{eco} derived from light-response curves (including daytime data)	Reduces influence of night-time data, may capture the effect of photo-inhibition of mitochondrial leaf respiration, if this exists (see Discussion)	Depends on specific light-response curve model; light-response curve can be confounded by other factors, e.g. air humidity, problem of equifinality of different solutions (resulting in high standard errors); R_{eco} estimate susceptible to storage flux problems, since those occur in the morning and evening during low-light conditions
1. R_{eco} as y-intercept from light-response curve of GEP (Falge *et al*., 2002a)	Day-to-day variation of R_{eco} reflected	Only daily R_{eco} can be derived
2. R_{eco} and GEP are simultaneously modelled as parts of one fixed model equation (Gilmanov *et al*., 2003)	Uses all data (night- and daytime)	Resulting GEP is from a model and thus constrained by model assumptions (disallows comparison with other models), temperature sensitivity maybe confounded by response of GEP to environmental factors, that are hard to separate; e.g. is afternoon drop in NEE caused by R_{eco} as $f(T)$ or by high VPD, or even by plant-internal hydraulic constraints?)
3. R_{eco} and GPP are simultaneously modelled as parts of one model equation with state dependent parameters (Data-based mechanistic modelling approach)	Uses all data (night- and daytime); very flexible approach; parameters can evolve with time and state	Statistical assumptions, e.g. non-correlated residuals, and robustness against violations may be problematic; maybe affected by confounding factors similar to B2.
4. R_{eco} and GPP are derived via *a posteriori* analysis of an artificial neural network conditioned with all data. (cf. Papale & Valentini, 2002 for gap-filling; flux-partitioning not explored)	Uses all data (night- and daytime); very flexible approach; influence of different input data can be evaluated for best description of the data set	Extrapolation problem, because zero radiation has to be assumed estimating R_{eco} from neural network during the day; potentially confounded by other factors similar to B2.

NEE, net ecosystem CO_2 exchange; VPD, vapour pressure deficit; GEP, gross ecosystem production.

Reichstein et al., 2005 GCB

A1: 基于全年夜间有效数据和单因子方程估算

$$NEE_{night} = \mathrm{Re}\,co_{night} = R_{ref} \cdot e^{E_0\left(\frac{1}{T_{ref}-T_0}-\frac{1}{T_K-T_0}\right)}$$ Lloyd & Taylor

or

$$NEE_{night} = \mathrm{Re}\,co_{night} = R_{ref} \cdot e^{\frac{E_A}{R}\left(\frac{1}{T_{ref}}-\frac{1}{T_K}\right)}$$ Arrhenius

or

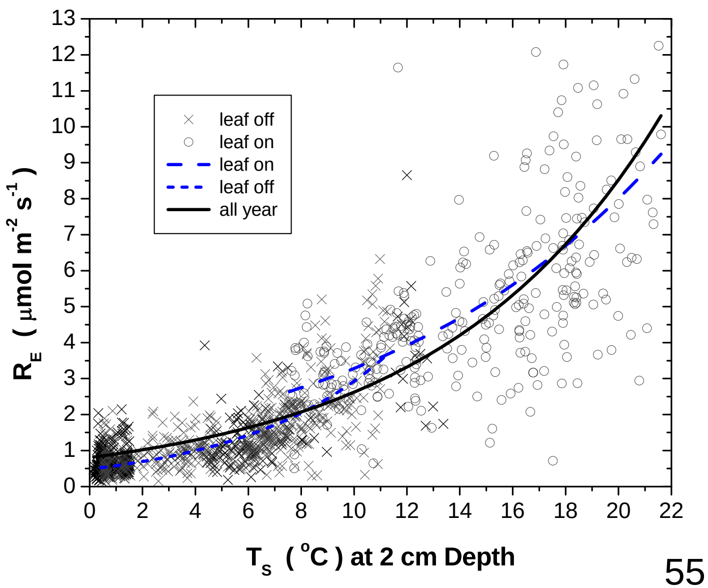
$$NEE_{night} = \mathrm{Re}\,co_{night} = A \cdot e^{(B \cdot T)}$$ Van't Hoff

优点:

- 简单、直接

缺点:

- 只考虑了土壤温度的影响
- 方程中的参数没有时间变化，可能会高估或低估不同时期的生态系统呼吸



A2: 基于全年夜间有效数据和双因子方程估算

Q10 Model

$$R_{eco} = R_{eco,refs}\,e^{\ln(Q_{10})(T_K - T_{ref})/10}$$

$$Q_{10} = a - bT_K + cS_w + dS_w^2$$

优点:

- 简单、直接
- 考虑了其它因子的影响

缺点:

- 需要考虑不同站点的具体限制因子，因此方程形式不具有普遍意义

A3: 基于全年数据估算生态系统呼吸敏感性，然后分时段估算参考温度下的生态系统呼吸

$$NEE_{night} = \mathrm{Re}\,co_{night} = R_{ref} \cdot e^{E_0\left(\frac{1}{T_{ref}-T_0}-\frac{1}{T_K-T_0}\right)}$$

Eo固定

R_{ref}随时间变化

优点:

- 考虑了参考温度下生态系统呼吸的季节变化

缺点:

- 基于全年估算的生态系统呼吸敏感性无法体现对环境变化的响应

A4: 分时段估算参考温度下的生态系统呼吸和生态系统呼吸敏感性

$$NEE_{night} = \mathrm{Re}\,co_{night} = R_{ref} \cdot e^{E_0\left(\frac{1}{T_{ref}-T_0}-\frac{1}{T_K-T_0}\right)}$$

Eo和R_{ref}随时间变化

优点:

- 考虑了参考温度下的生态系统呼吸和生态系统呼吸敏感性的季节变化以及环境响应

缺点:

- 不同时段内数据质量和数量，以及时段内的温度跨度影响了参数拟合
- 可行性比较低

A5: 分时段估算和确定全年生态系统呼吸敏感性，分时段估算参考温度下的生态系统呼吸

Short term exponential method

$$NEE_{night} = \mathrm{Re}\,co_{night} = R_{ref} \cdot e^{E_0\left(\frac{1}{T_{ref}-T_0} - \frac{1}{T_K - T_0}\right)}$$

Eo固定

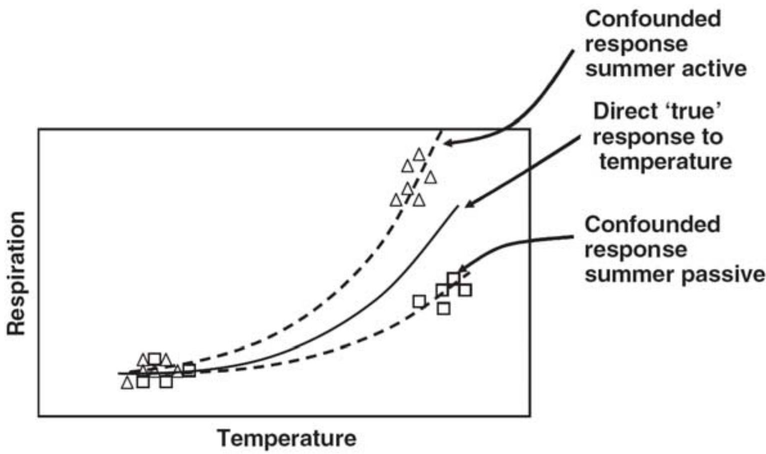
R_{ref}随时间变化

优点:

- 考虑了参考温度下的生态系统呼吸的季节变化和环境响应
- 通过分时段估算，综合考虑和确定了生态系统呼吸敏感性

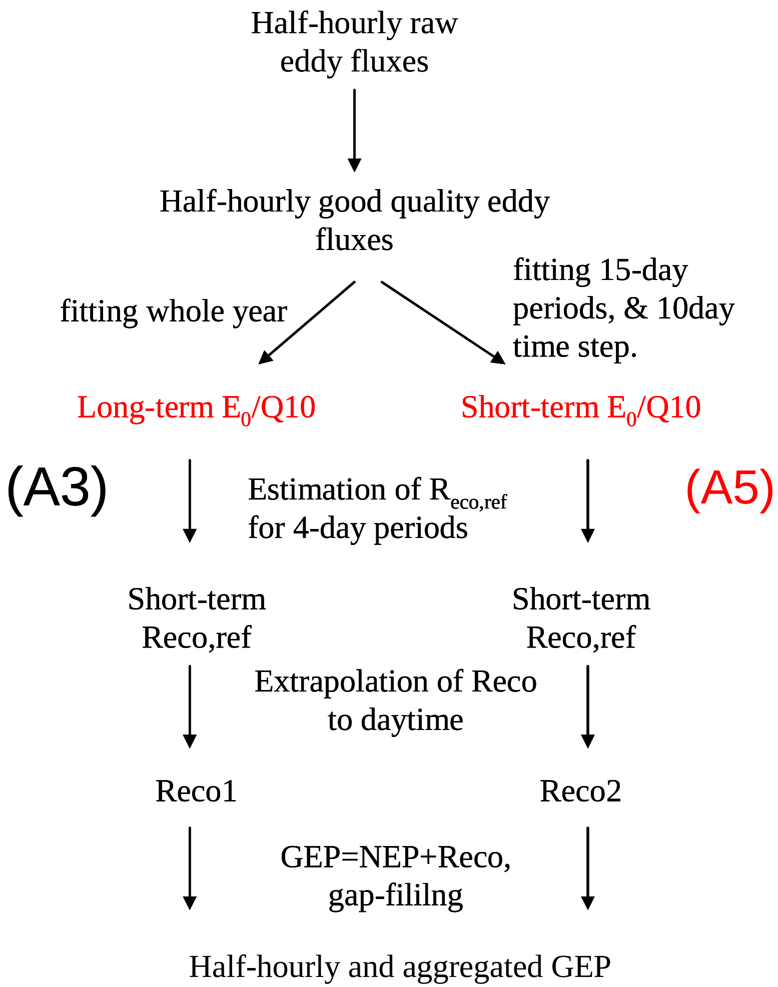
缺点:

- 基于全年估算的生态系统呼吸敏感性无法体现对环境变化的响应



Reichstein et al., 2005

Short term exponential method



$$R_{eco} = R_{ref} \cdot e^{E_0 \cdot \left(\frac{1}{T_{ref} - T_0} - \frac{1}{T_{soil} - T_0} \right)}$$

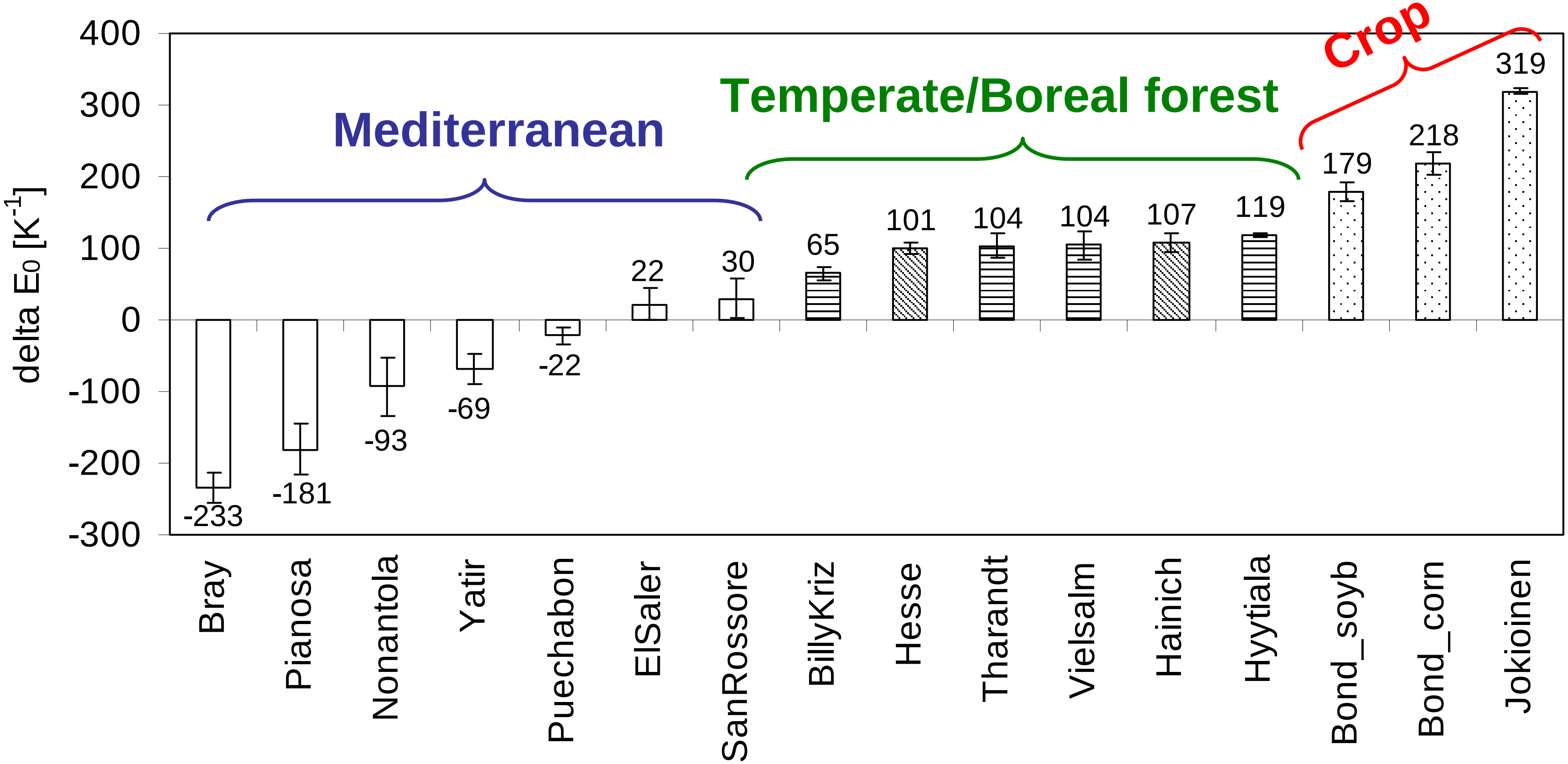
- R_{ref} =参考温度下的生态系统呼吸 (10^{o}C)
- E_0 = 活化能，表征温度敏感性
- T_{ref} = 参考温度 = 10^{o}C
- T_0 = 基点温度 = -46.02^{o}C
- T_{soil} = 土壤温度 ^{o}C

Reichstein et al., 2005

Short term exponential method计算流程

- 将全年夜间数据按15天窗口分组，时间窗口每次移动5天，即相邻两个窗口有10天的重叠；
- 拟合方程参数之前，先检查时间窗口内的有效数据量（>6）和温度跨度（>5^{o}C）；如果不能满足，则移动到下一个窗口；
- 所有有效时间窗口的参数拟合后，选择生态系统呼吸温度敏感性（Eo）的相对标准差最小的3个拟合参数取平均数（$E_{o,short}$），或者以相对标准差做权重计算$E_{o,short}$；
- $E_{o,short}$确定之后，将全年夜间有效数据按4天的时间窗口分组，拟合得到每个时段的R_{ref}，没有拟合的时段利用线性内插的方法插补。
- $E_{o,short}$和R_{ref}确定之后，即可估算生态系统呼吸。

不同方法估算的E_0

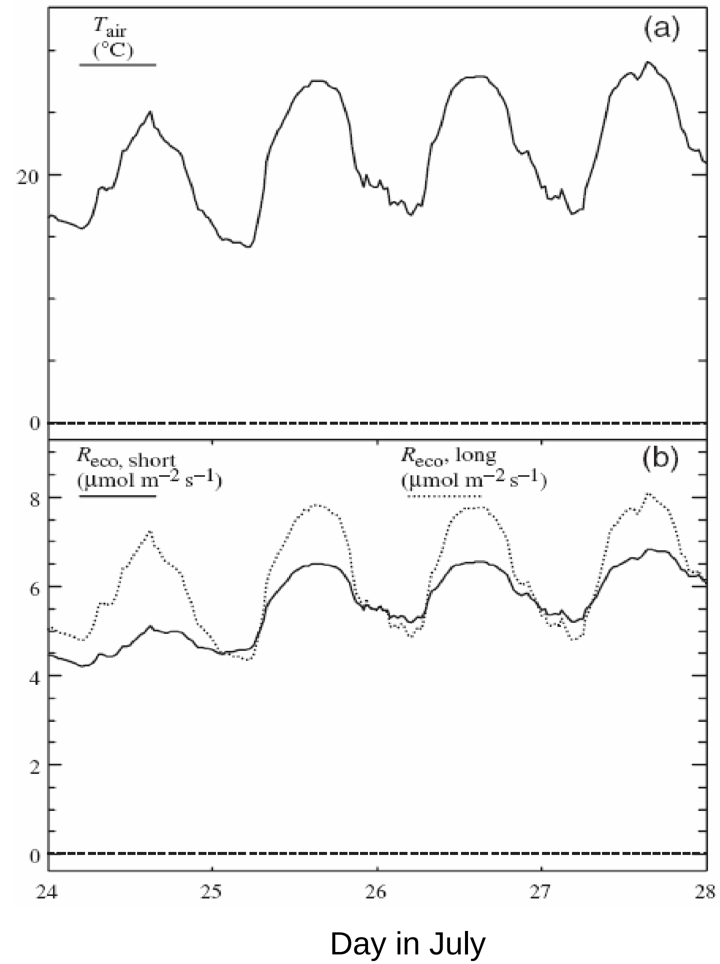


Reichstein et al., 2005

E_o不同估算方法对生态系统呼吸的影响

基于全年估算的Eo（ Eo,long ）和基于分时段计算的Eo（ Eo,short ）的对比 （站点：Hesse, France 2001 Deciduous Beech Forest）

- $E_{o,short}$ = 104 K^{-1}
- $E_{o,long}$ = 205 K^{-1}
- 当 T_{air} >> T_{ref}时，Reco的估算误差大部分是由于Eo的误差引起，所以Eo的高估会导致Reco的过高估算。



Reichstein et al., 2005

（2）利用白天观测数据估算

B1：单因子方法

利用白天通量数据和辐射的光响应方程推算生态系统呼吸

$$NEE_{day} = \frac{a' \cdot Q_{PPFD} \cdot F_{GPP,sat}}{F_{GPP,sat} + a' \cdot Q_{PPFD}} - F_{RE,day}$$

直角双曲线方程

$$NEE_{night+day} = -\frac{2}{2\eta}\left(\alpha Q + \beta - \sqrt{(\alpha Q + \beta)^2 - 4\alpha\beta\eta Q}\right) + \gamma$$

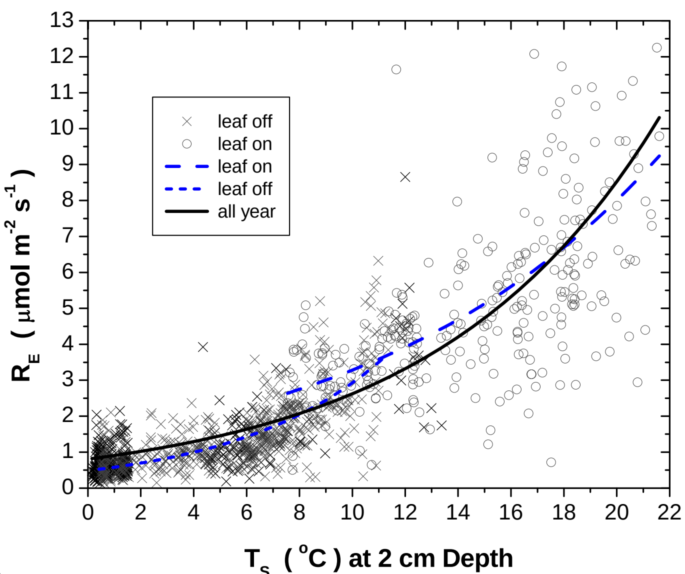
非直角双曲线方程

优点:

- 简单
- 不考虑夜间数据质量

缺点:

- 没有考虑其它因子的影响
- 在估算窗口内，Reco是定值
- 不同形式的光响应方程的估算结果有一定差异



B2：多因子方法

$$P(Q,T;\alpha,A_{\max},r_d,\theta,r_0,k_T) = \frac{1}{2\theta}\left(\alpha Q + A_{\max} - \sqrt{(\alpha Q + A_{\max})^2 - 4\alpha A_{\max}\theta Q}\right) - r_0\,\mathrm{e}^{k_T T}, \tag{9}$$

Gilmanov et al., 2007, AFM

$$\mathrm{NEE} = \frac{\alpha\beta \mathrm{R_g}}{\alpha \mathrm{R_g} + \beta} + rb\exp\left(E_0\left(\frac{1}{T_{\mathrm{ref}} - T_0} - \frac{1}{\mathrm{T_{air}} - T_0}\right)\right). \tag{3}$$

Lasslop et al., 2010, GCB

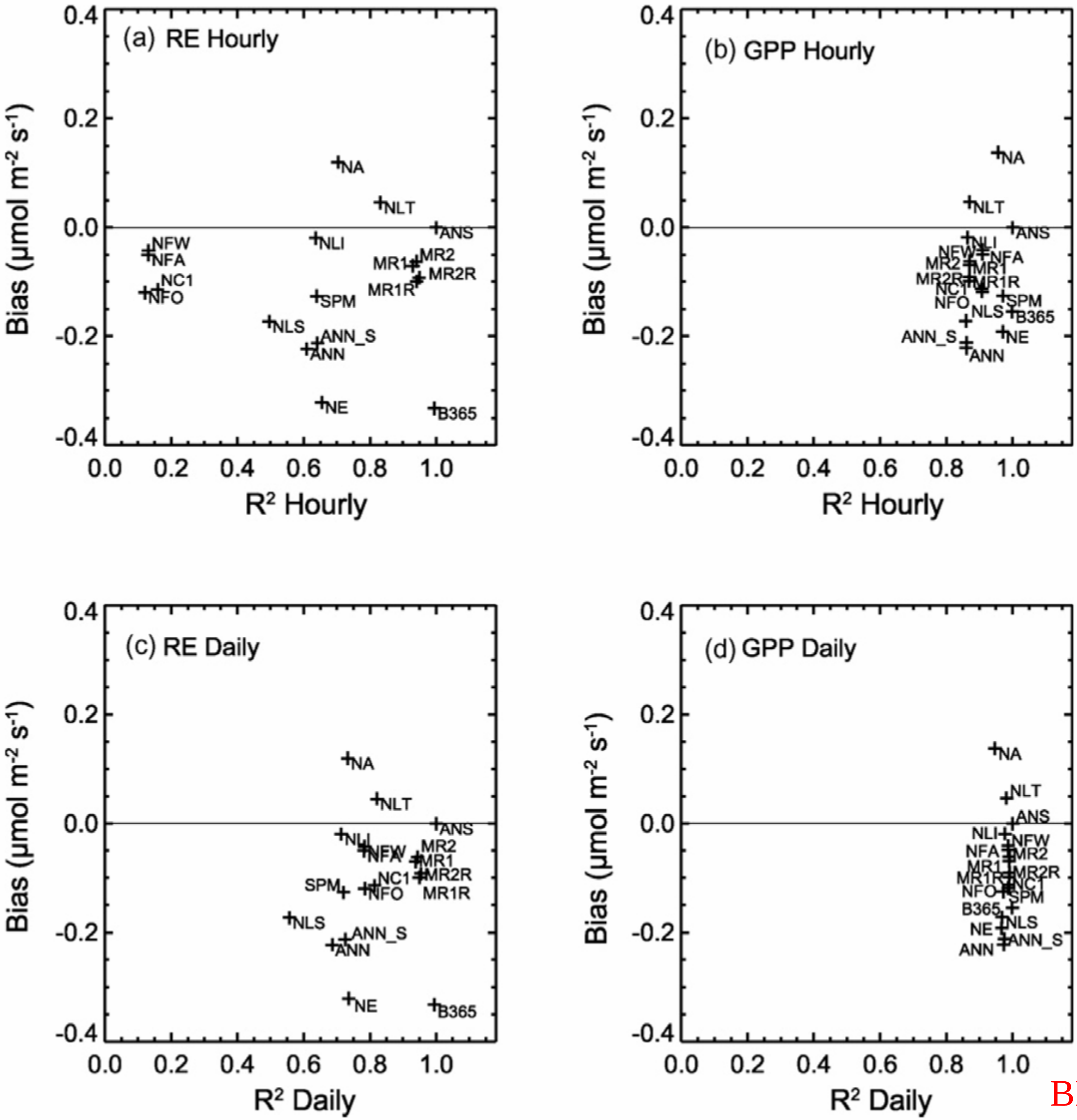
$$\beta = \begin{cases} \beta_0 \exp(-k(\mathrm{VPD} - \mathrm{VPD_0})), & \mathrm{VPD} > \mathrm{VPD_0}, \\ \beta = \beta_0, & \mathrm{VPD} < \mathrm{VPD_0}. \end{cases} \tag{4}$$

Table 1 – List of methods used to derive GPP and RE for all sites. Detailed descriptions can be found in Moffat et al. (2007) or the noted citation. Abbreviations used by Moffat et al. (2007) are noted in italics

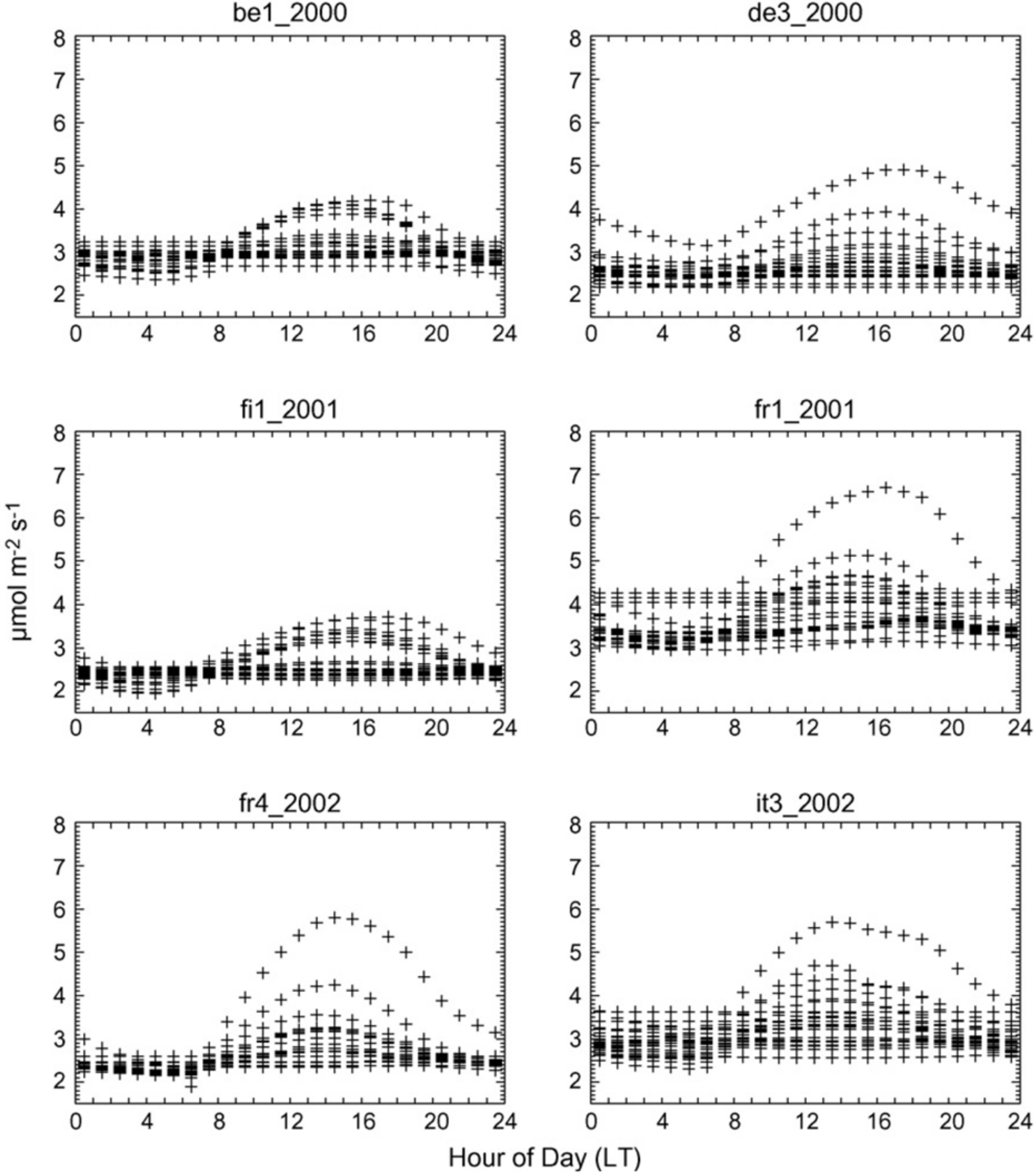
Abbreviation	Description	Citation
Non-linear regression		
NA (*NLR_AM*)	Noormets model	Noormets et al. (2007)
NE (*NLR_EM*)	Eyring respiration model	Desai et al. (2005)
NFA (*NLR_FM_AD*)	Absolute deviation model	Richardson et al. (2006a)
NFO (*NLR_FM_OLS*)	Ordinary least squares model	Richardson et al. (2006a)
NFW[a]	Weighted absolute deviation model	Richardson et al. (2006a)
NLI	Light intercept based regression	Falge et al. (2001)
NLT (*NLR_LM*)	Air temperature based regression	Falge et al. (2001)
NLS	Soil temperature based regression	Falge et al. (2001)
NC1 (*NLR_FCRN*)	Multi timescale regression	Barr et al. (2004)
NC2[b]	Multi timescale regression	Barr et al. (2004)
MR1	Long term air temperature regression	Reichstein et al. (2005)
MR1R	Robust long term air temperature	Reichstein et al. (2005)
MR2	Short term air temperature regression	Reichstein et al. (2005)
MR2R	Robust short-term air temperature	Reichstein et al. (2005)
Lookup tables/mean diurnal course		
NLID	Diurnal course with light intercept	Falge et al. (2001)
NLIL	Lookup table with light intercept	Falge et al. (2001)
NLTD (*MDV*)	Diurnal course with air temperature	Falge et al. (2001)
NLTL (*LUT*)	Lookup table with air temperature	Falge et al. (2001)
NLSD	Diurnal course with soil temperature	Falge et al. (2001)
NLSL	Lookup table with soil temperature	Falge et al. (2001)
Other methods		
B365 (*BETHY_ALL*)	Ecosystem model inversion	Knorr and Kattge (2005)
SPM (*SPM*)	Semi-parametric method	Stauch and Jarvis (2006)
UKF[b] (*UKF_LM*)	Unscented Kalman filter	Gove and Hollinger (2006)
ANN (*ANN_PS*)	Artificial neural network	Papale and Valentini (2003)
ANNS[a]	Artificial neural network with soil moisture	Papale and Valentini (2003)

[a] Method used only for synthetic analysis.
[b] Method not used in synthetic analysis.

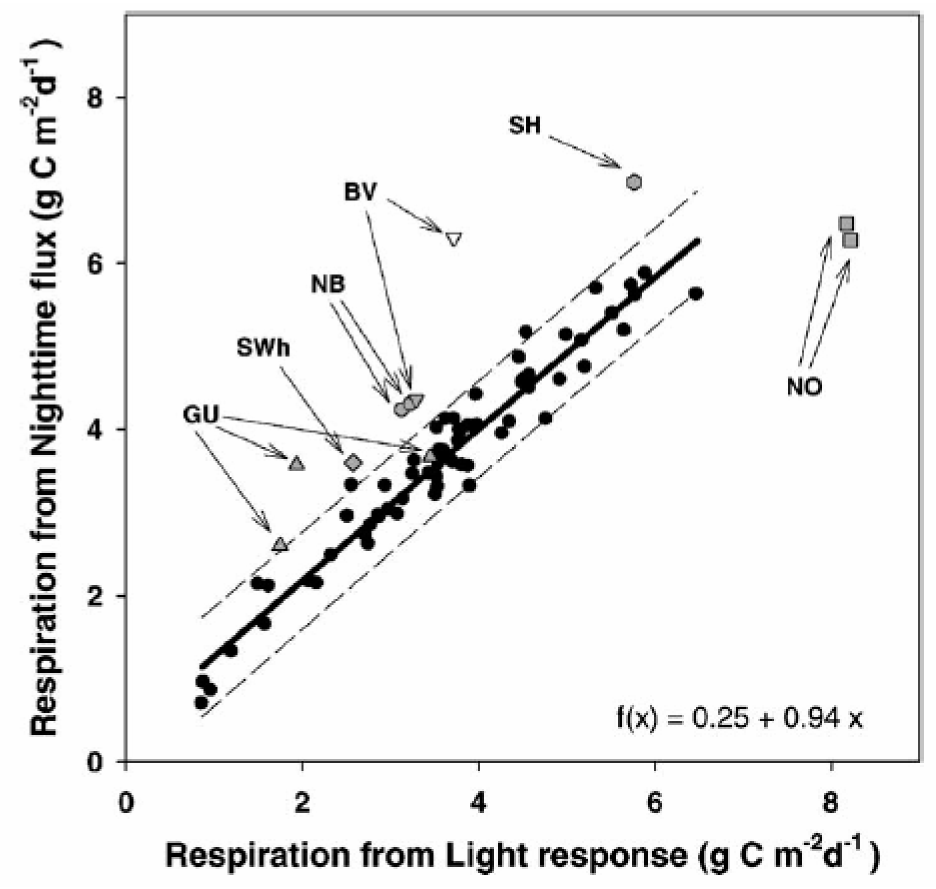
Desai et al., 2008, AFM


(a) RE Hourly
(b) GPP Hourly
(c) RE Daily
(d) GPP Daily
Bias (μmol m-2 s-1)
R2 Hourly
R2 Daily
NA
NLT
ANS
NLI
NFW
NFA
NC1
NFO
MR1
MR2
MR2R
MR1R
SPM
NLS
ANN_S
ANN
NE
B365

BETHY model


be1_2000
de3_2000
fi1_2001
fr1_2001
fr4_2002
it3_2002
μmol m-2 s-1
Hour of Day (LT)

两种生态系统呼吸估算方法的结果对比



Fagle et al., 2002 AFM

拆分方法小结

- 不同的站点适合不同的拆分方法（取决于观测数据质量和有效数据数量）
- 不同的拆分方法可能适合不同的研究目的；
- 不同的拆分方法可能产生不同的GEP和Reco
- 其它方法的对比，如箱式法观测的生态系统呼吸。

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