Emergent Temperature Sensitivity of SOM Decomposition Depends on Interactions Between Minerals, Substrates, Enzymes, and Microbes

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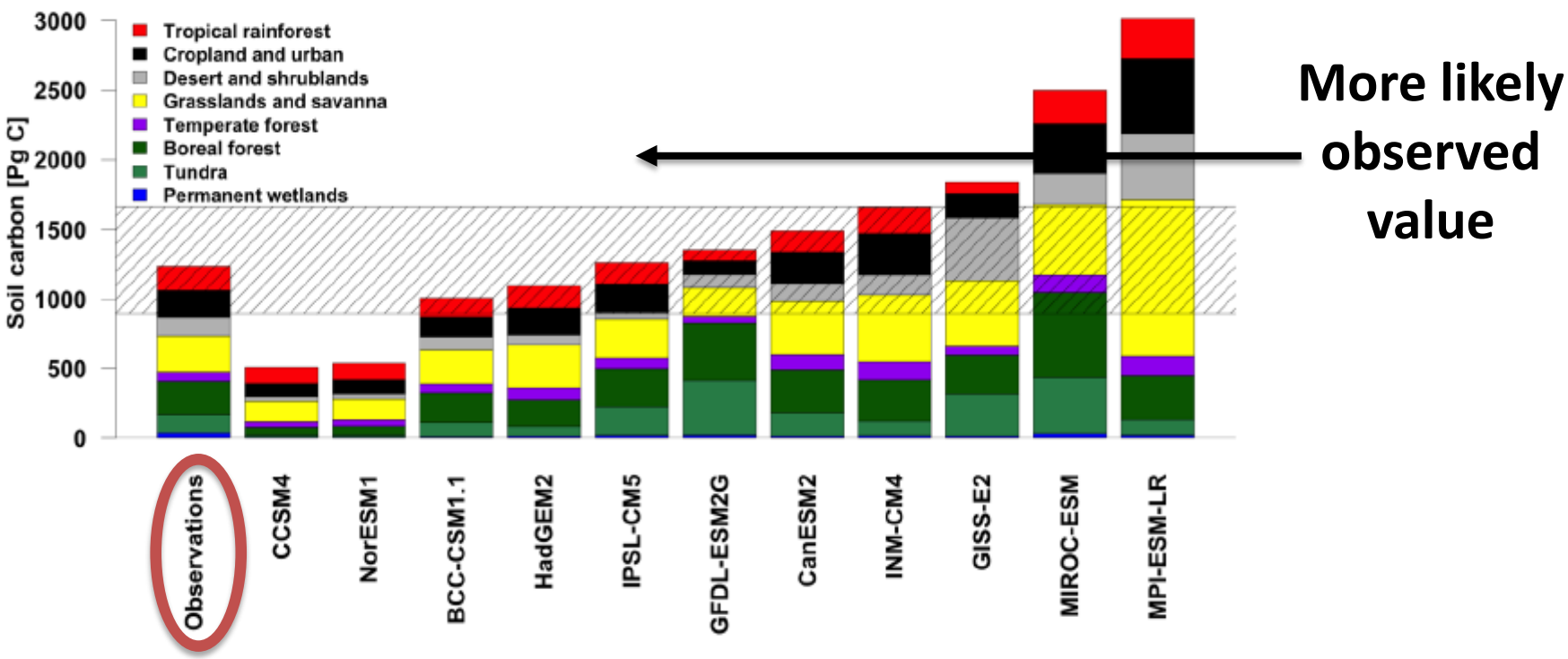
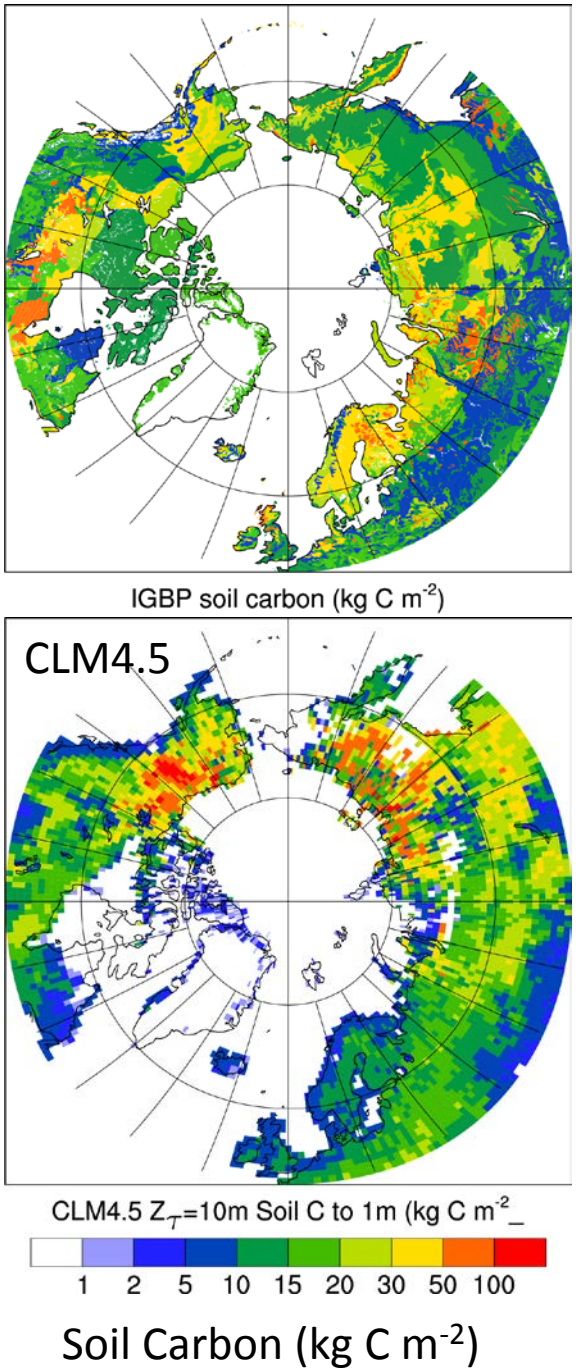
NGEE-Arctic All Hands Meeting, Saturday, December 13, 2014

Motivation

- Soils store several times more carbon than either the atmosphere or terrestrial vegetation
  - C-climate feedbacks are critical for climate prediction
  - Wide range of predictions for soil carbon stocks and changes over the 21st century (Todd-Brown et al., 2013)



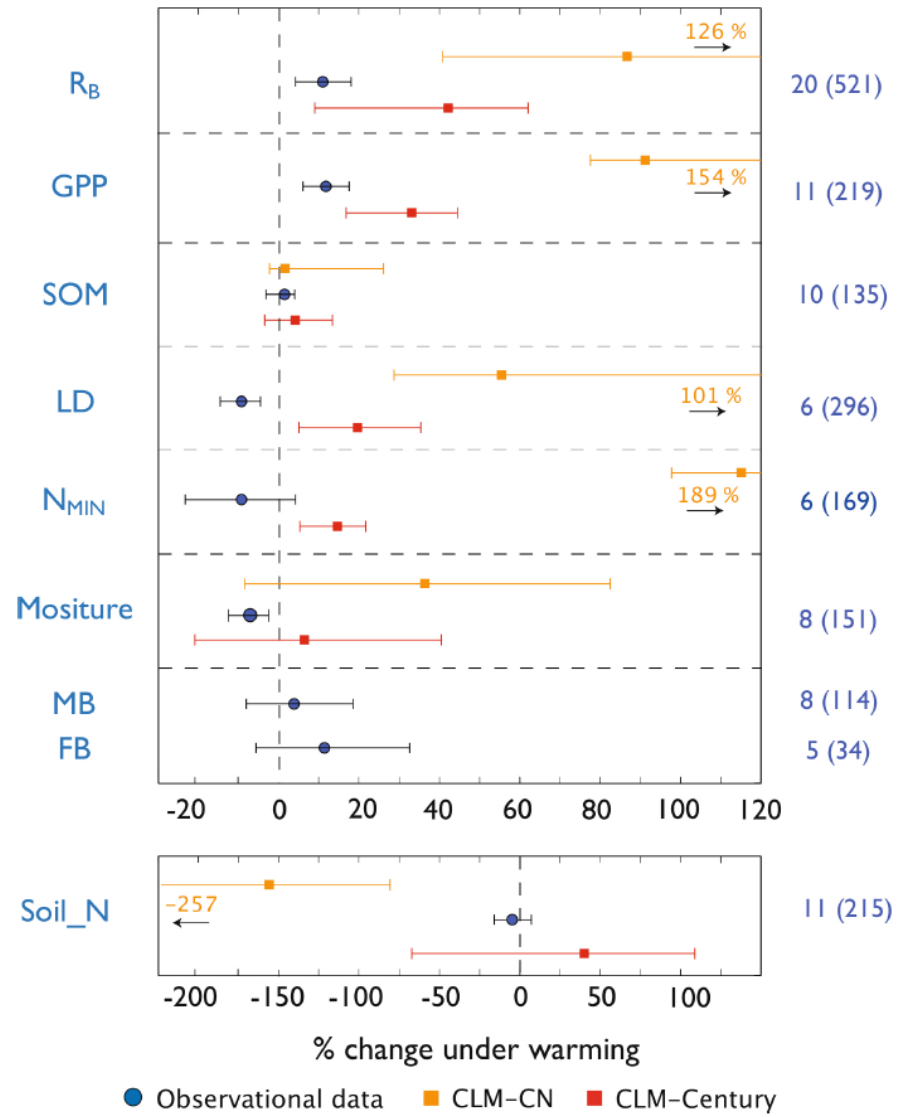


- However, large problems persist in CLM4.5
  - Alaskan SOM spatial structure: Mishra and Riley (in review *Vadose Zone J.*)
  - Pan-Arctic and global distributions of SOM, GPP, LAI, etc.
- We hypothesize that a big part of the problem lies in the methods used to represent nutrient dynamics, losses, and impacts on plant processes
  - See Bardan Ghimire's and Chonggang Xu's posters here

MODEX Belowground Motivation

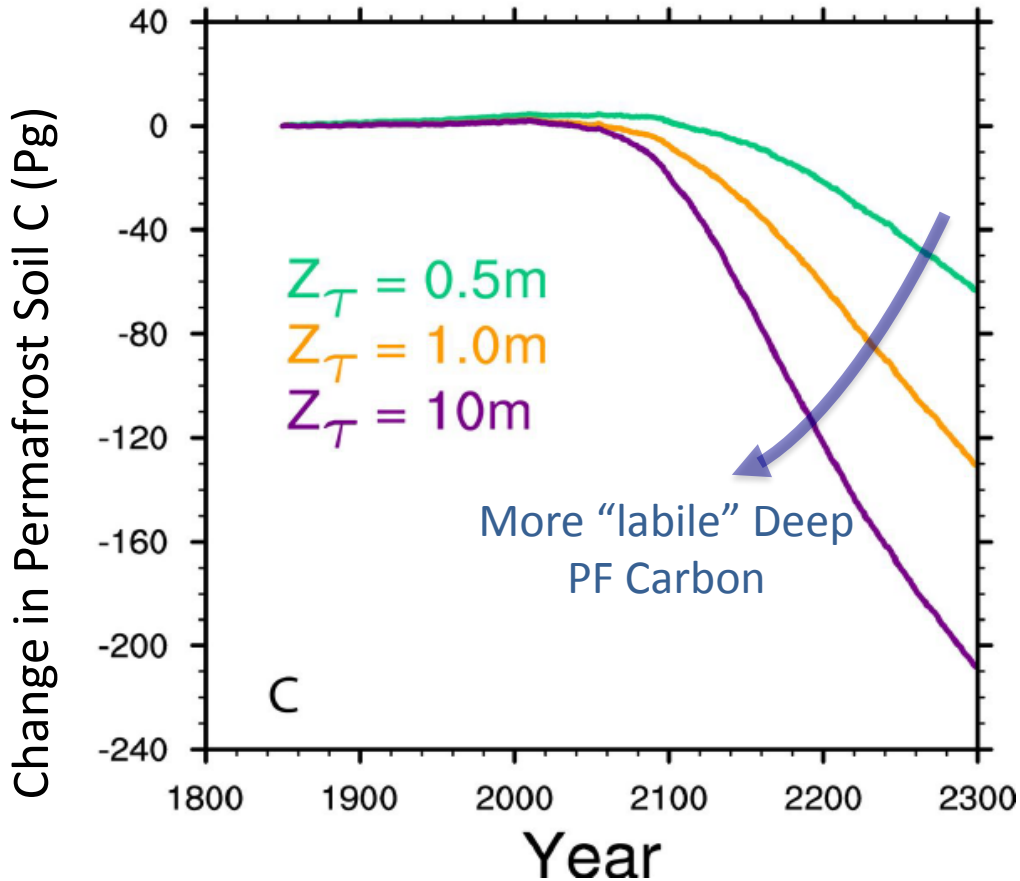
- Clearly, problems remain with:
  - Representation of soil C, nutrient biogeochemistry, and nutrient competition

Arctic tundra warming and N addition meta-analysis compared with CLM (Bouskill et al., 2014; *Biogeosciences*)



Resolving these issues is critical to developing good NGEE-Arctic Carbon cycle predictions

Koven et al. (in review *PNAS*)



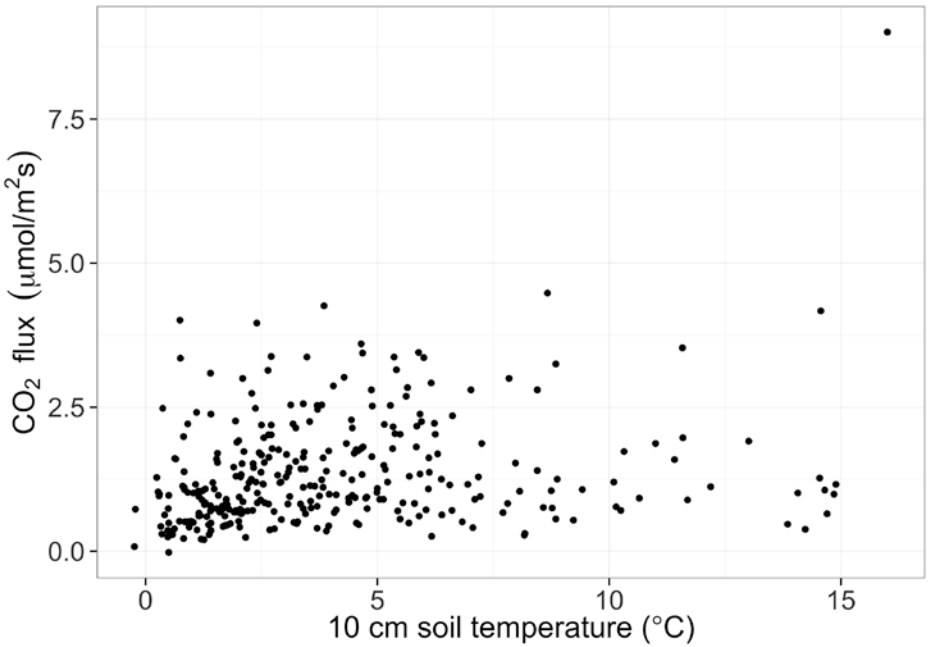
Thaw depth, nutrient release, competition with plants result in very large differences in ecosystem C stocks

SOM Models

- Current pseudo-first-order model structures:
  - Based on comparisons with equilibrium carbon stocks
  - Impose static functions for temperature sensitivities based on incubation or field studies
  - Largely ignore abiotic and microbial controls
- Vertically-resolved microbe-enabled models (MEMs) for SOM dynamics pose alternative hypotheses (Riley et al. 2014 *GMD*; Dwivedi et al. poster)
- These models have different levels of mechanistic representation and also perform very differently
  - What level of MEM complexity is required to resolve SOM dynamics?

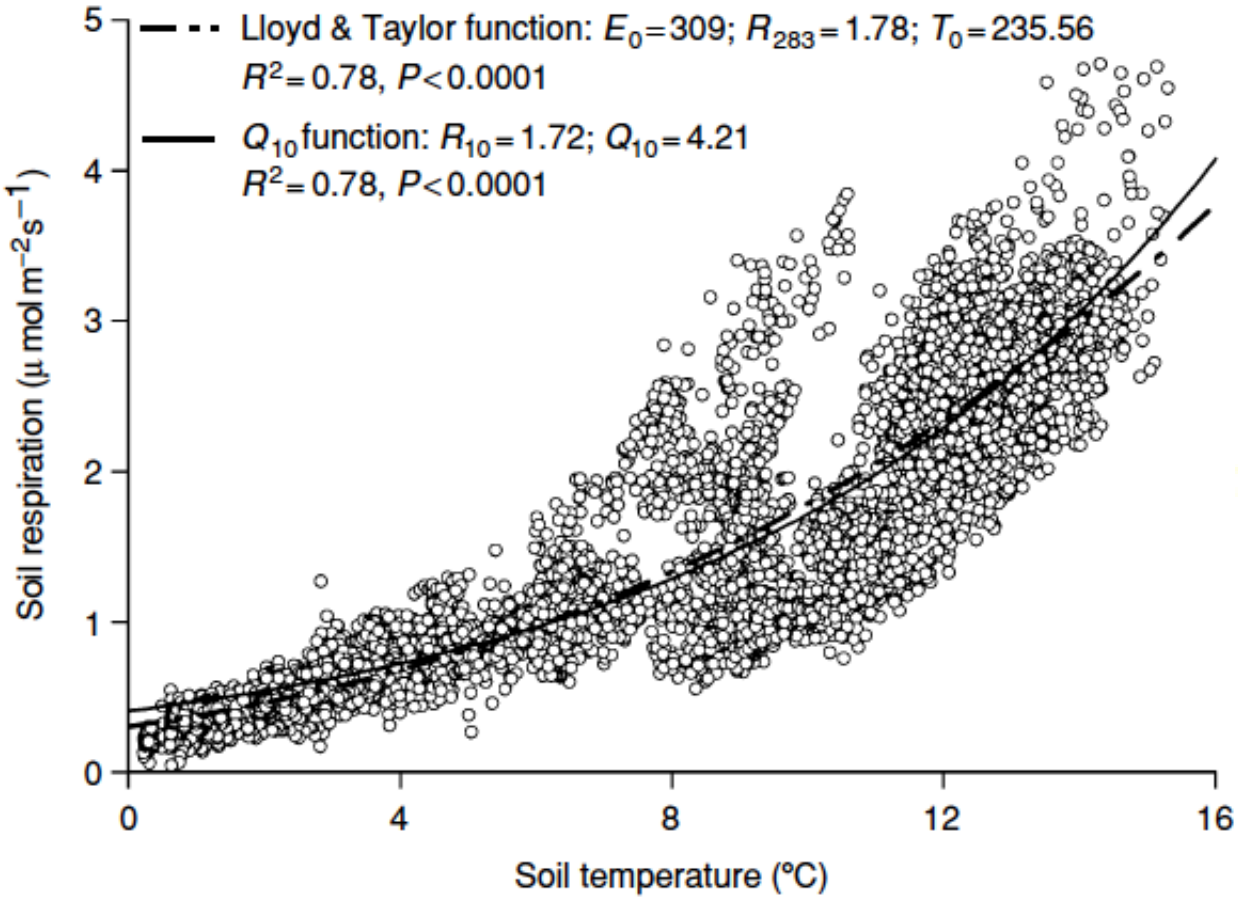
Observations Imply Highly Variable Q_{10}

- Surface CO_2 flux measurements from 48 profiles at the NGEE-Arctic sites
  - Centers, edges, and troughs
  - 16 polygons in areas A, B, C, and D
  - Repeated measurements during July, August, and September 2013



- Chowdhury et al. (2014) found Q_{10} varying from 1.6 to 7.1 for CO_2 temperature sensitivity using laboratory incubations of soils from the NGEE-Arctic sites

Observations Imply Highly Variable Q_{10}

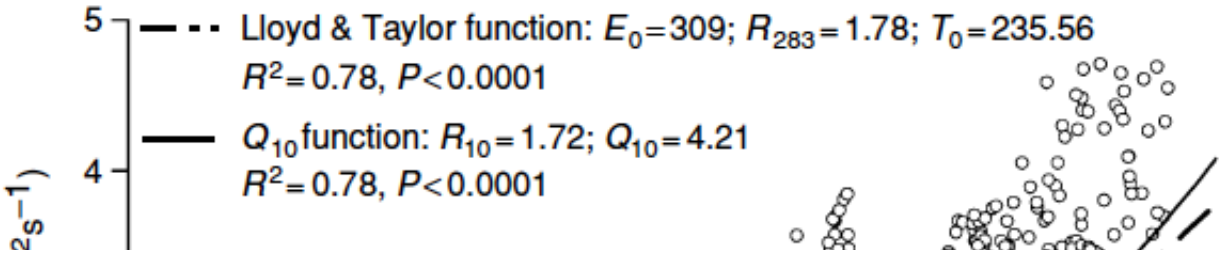


Q_{10} = 4.2 for entire record
Q_{10} = 3 for summer
Q_{10} = 23 in winter

$$SR = R_{10} * Q_{10}^{((T-10)/10)}$$

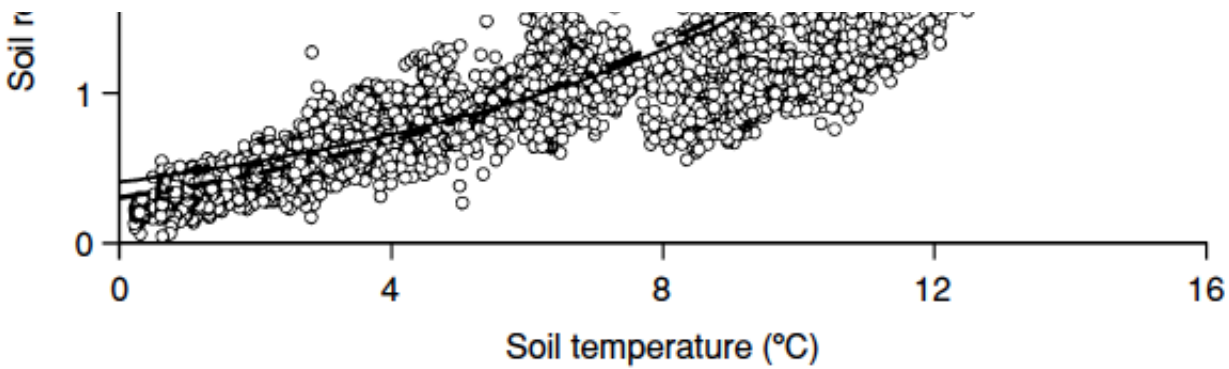
Beech Forest
Janssens & Pilegaard, 2003

Observations Imply Highly Variable Q_{10}



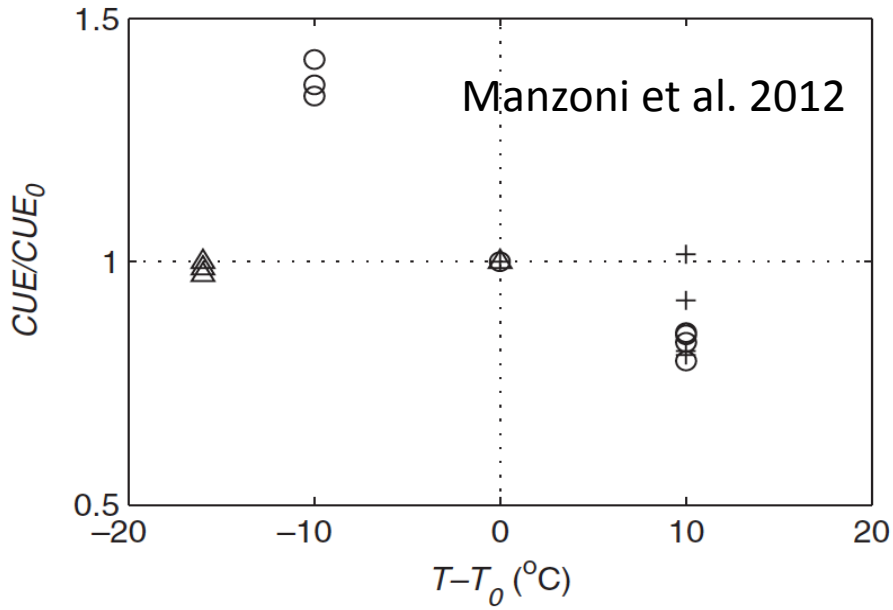
Q_{10} = 4.2 for entire record
Q_{10} = 3 for summer
Q_{10} = 23 in winter

"If soil respiration needs to be simulated over time periods from days to weeks, …, more short-term parameterization is required"



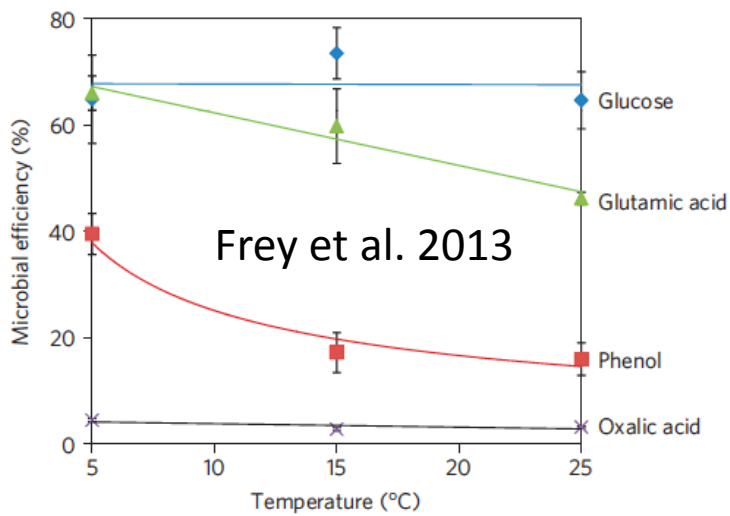
Beech Forest
Janssens & Pilegaard, 2003

CUE Temperature Sensitivity Also Highly Variable



	CUE
4 °C	0.73 (0.004)
20 °C	0.75 (0.002)
P	<0.05

Dijkstra et al. 2011



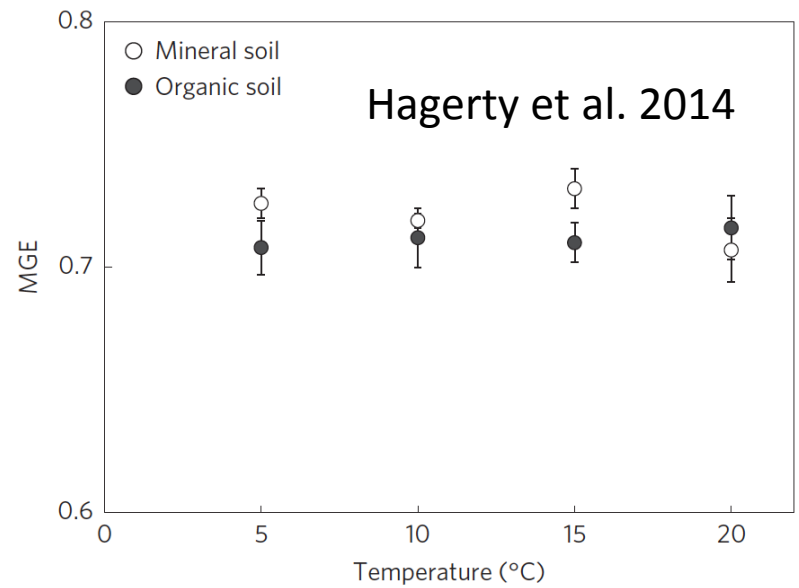
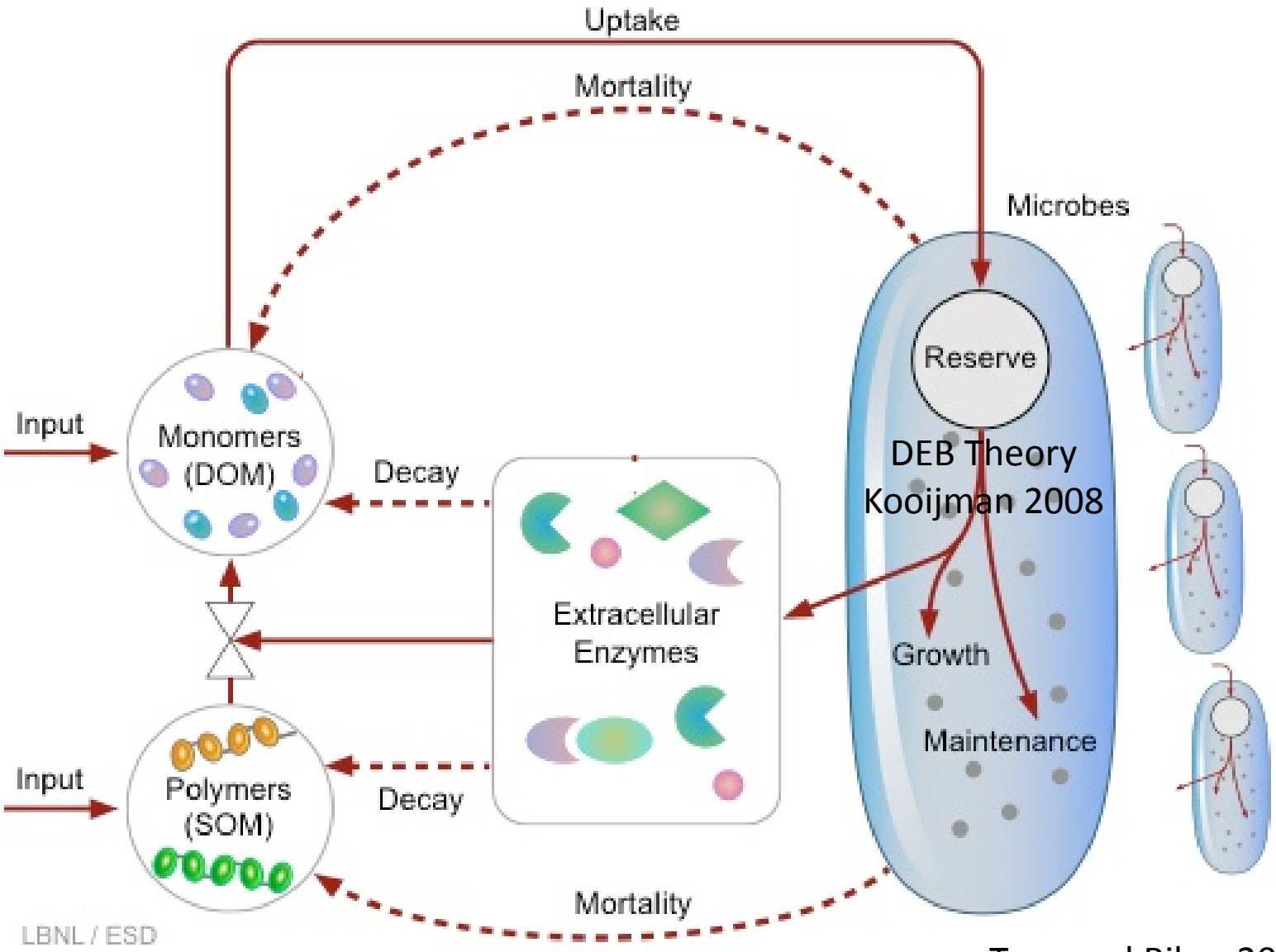


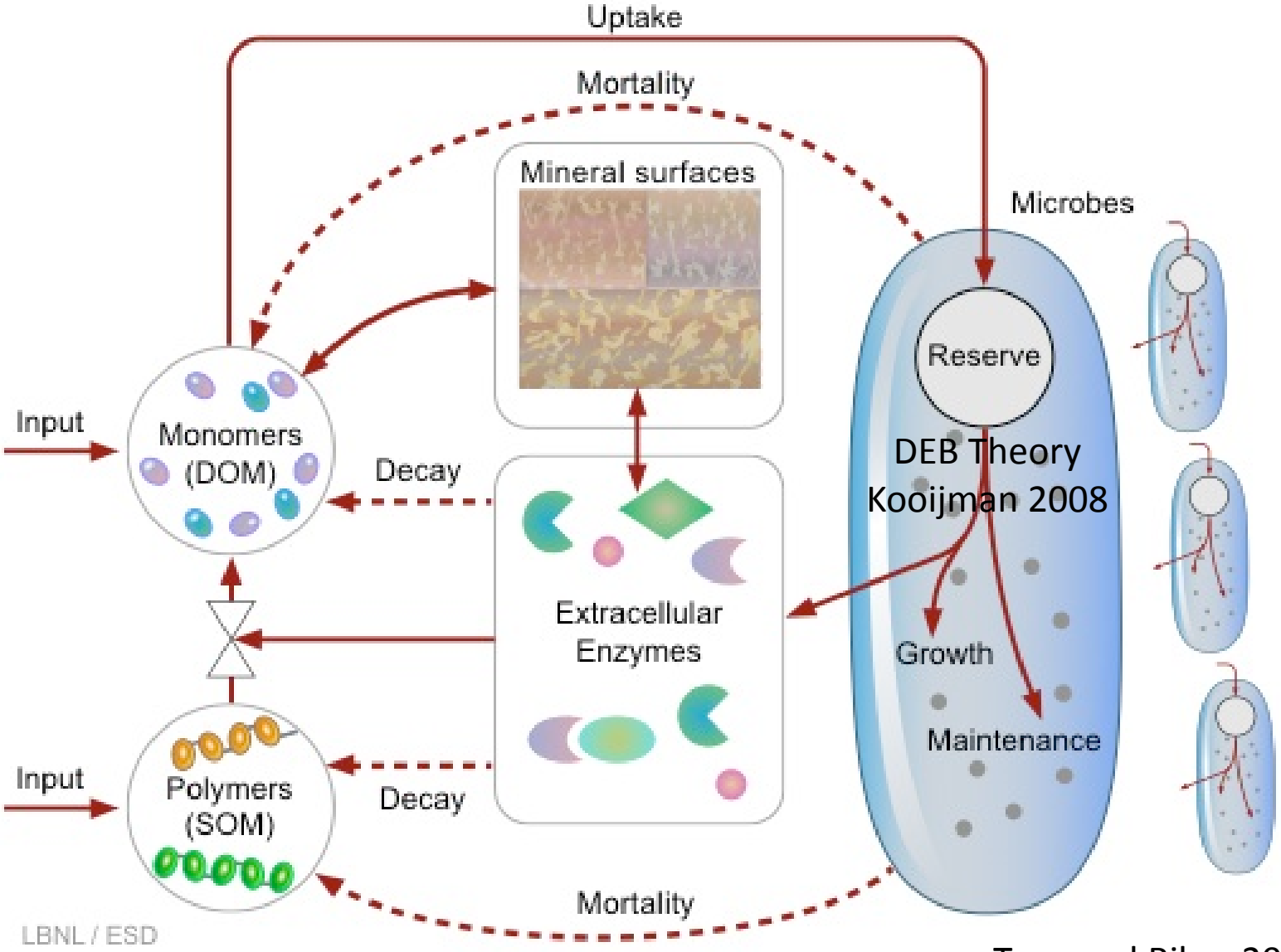
Figure 1 | Microbial growth efficiency (MGE) after a 7-day incubation at different temperatures for a mineral and an organic soil. Means and

Microbe-Explicit Model



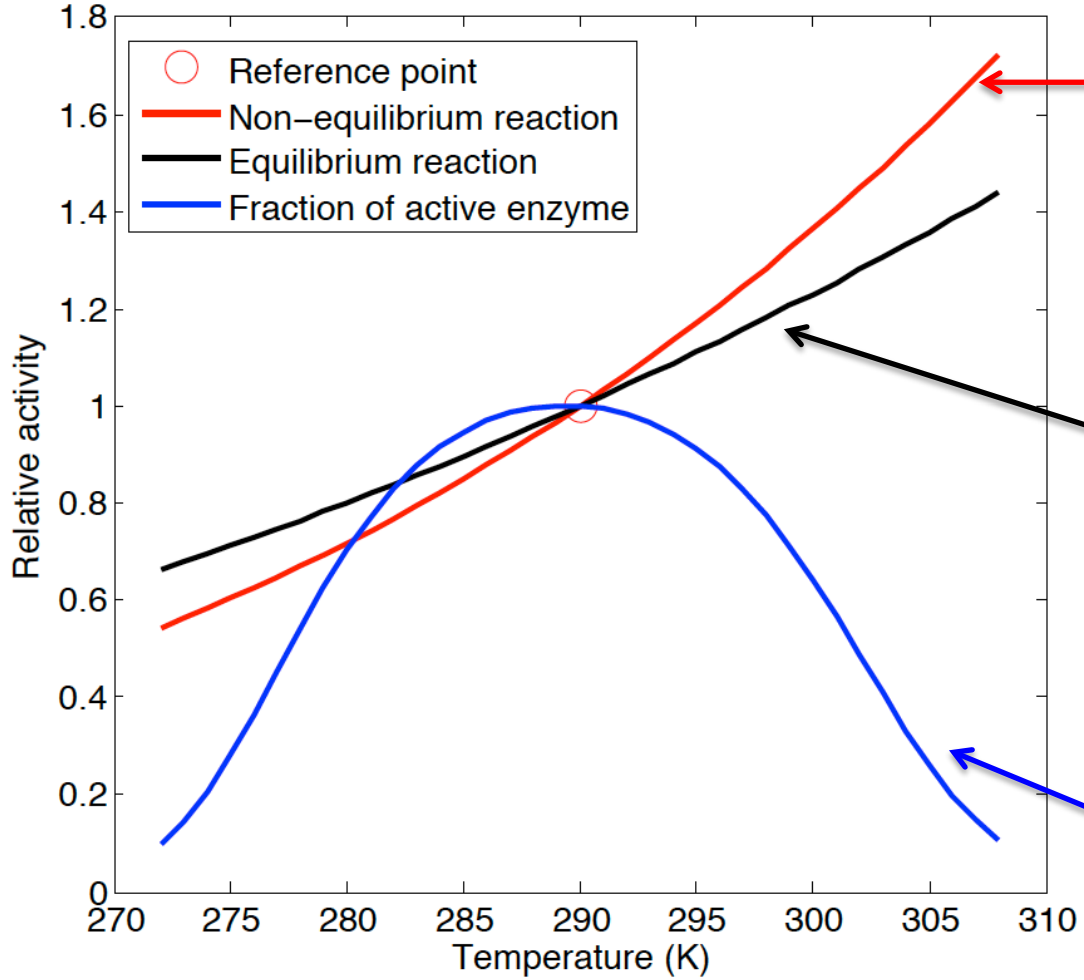
Tang and Riley, 2014, *Nature CC*

+ Mineral-Surface Interactions



Tang and Riley, 2014, *Nature CC*

Temperature Sensitivities

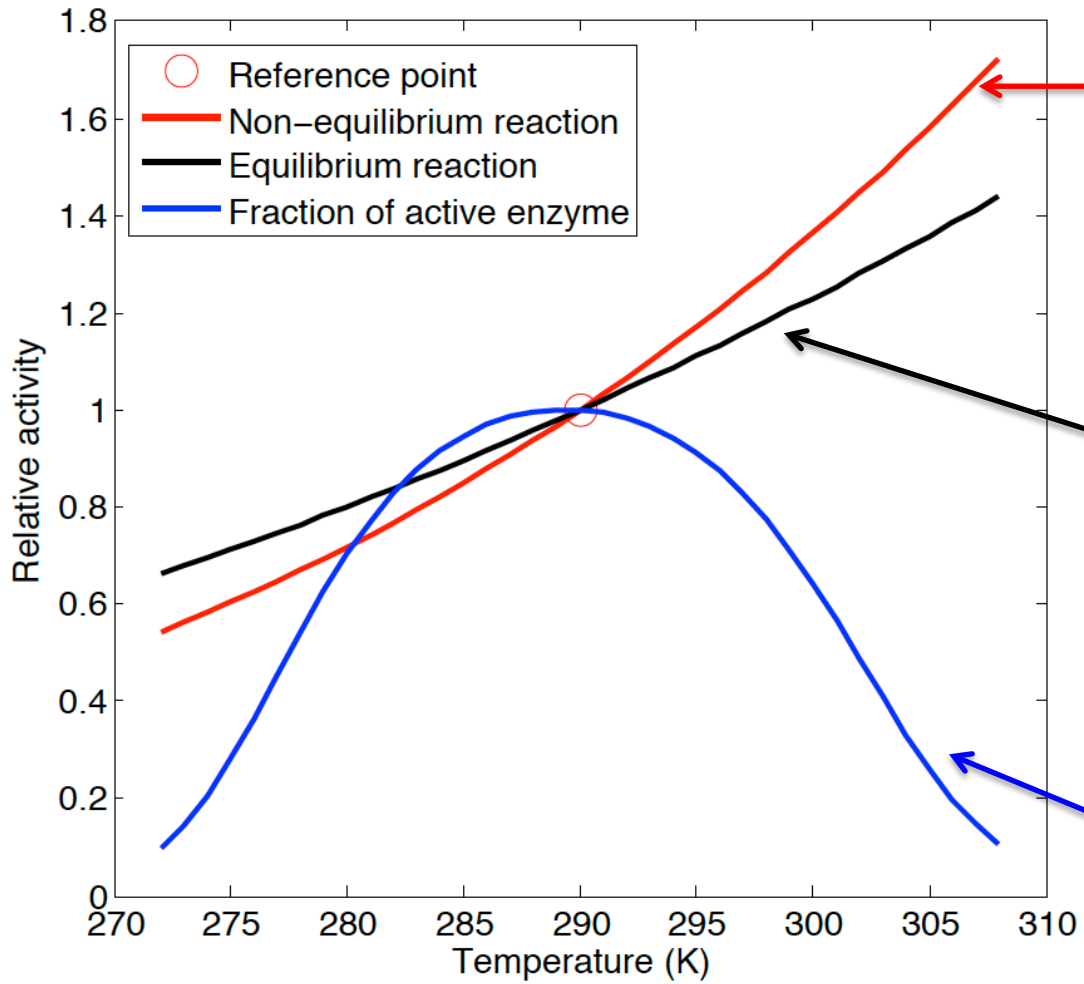


Transition state theory: substrate conversion

Arrhenius rate law: reversible binding processes, cell maintenance

Enzyme stability

Temperature Sensitivities



Transition state theory: substrate conversion

Arrhenius rate law: reversible binding processes, cell maintenance

Enzyme stability

See Maggi and Riley (2014, *Biogeosciences Discussion*) for a MODEX approach using nine independent denitrification experiments, the Arrhenius rate law, and Eyring's transition-state theory to estimate temperature impacts on reaction rate constants, affinities, and kinetic isotopic effects.

Competition

- Soil BGC dynamics depend on functional and trait-based microbial processes (Bouskill et al. 2012, *Frontiers Microbiology*)
- Competition in a consumer-substrate network can be formulated as an equilibrium chemistry problem (Tang and Riley 2013, *Biogeosciences*)
  - Numerical solution is computationally expensive
- First-order accurate EC approximation (ECA)
  - ECA improves upon the widely used Michaelis-Menten representation of enzyme-substrate kinetics for complex systems
  - Generalizable to, e.g., nutrient interactions and predator-prey systems

ECA Kinetics

$$\tilde{C}_{ij} = \frac{S_{i,\mathrm{T}} E_{j,\mathrm{T}}}{K_{\mathrm{S},ij}\left(1 + \sum_{k=1}^{k=I} \frac{S_{k,\mathrm{T}}}{\tilde{K}_{\mathrm{S},kj}} + \sum_{k=1}^{k=J} \frac{E_{k,\mathrm{T}}}{\tilde{K}_{\mathrm{S},ik}}\right)}$$

Method facilitates inclusion of an arbitrary number of inhibitory mechanisms, microbial traits, and sorption

$$\tilde{K}_{\mathrm{S},ij} = \frac{K_{\mathrm{S},ij}}{\sum_{k=1}^{k=L} \frac{I_{k,\mathrm{T}}}{K_{I,ijk}} + 1}$$

$$\tilde{K}_{\mathrm{S},ij} = K_{\mathrm{S},ij}\left(1 + \frac{V_{\mathrm{max},ij}}{4\pi D_i r_{\mathrm{c},j} n_j K_{\mathrm{S},ij}}\right)$$

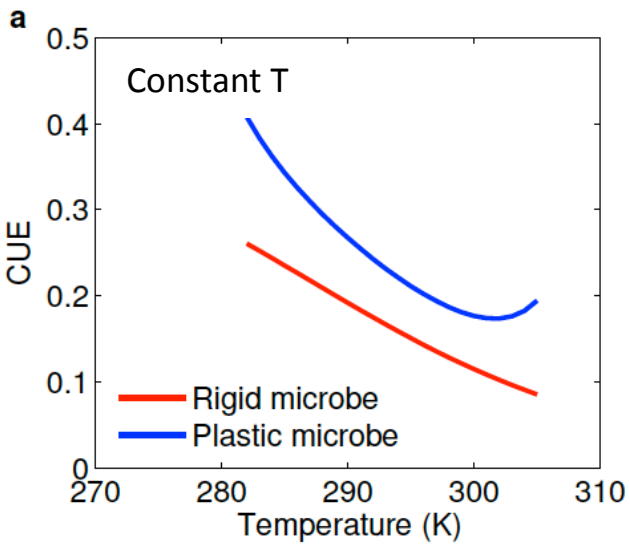
(Tang and Riley 2013, *Biogeosciences*)

ID	Model prediction	Example empirical studies
1	Total SOM stock increases with mineral surface protection capacity (Figure S12b)	Torn *et al.* [30], Sollins *et al.* [31]
2	Total SOM stock increases with carbon input rate (Figure S12a)	Liao *et al.* [32], Hungate *et al.* [33]
3	Decomposition rate per unit total SOM mass decreases with mineral surface protection capacity (Figure 1)	Jenkinson and Coleman [34]
4	CUE is highly variable (Figures 2)	Lopez-Urrutia and Moran [35], Sinsabaugh *et al.* [36]
5	Decomposition temperature sensitivity has seasonal variability (Figures 1 and S4)	Janssens and Pilegaard [37]
6	There is an optimal temperature for decomposition (Figures 1, S6 and S11)	Balser and Wixon [38]
7	Respiration temperature response is asymmetric (Figures 1, S4, S6 and S11)	Balser and Wixon [38]
8	Decomposition temperature sensitivity is higher at lower temperature (Figure S4)	Hamdi *et al.* [39]
9	"Labile" carbon can be preserved for long periods (Figure S13)	Klebber *et al.* [40]
10	"Recalcitrant" carbon decomposition is more temperature sensitive (Figures S6)	Conant *et al.* [27]
11	Under otherwise equivalent conditions, decomposition temperature sensitivity increases with higher substrate activation energy (Figure S4)	Conant *et al.* [27]
12	Temporal average could underestimate decomposition temperature sensitivity (Figure S4)	Janssens and Pilegaard [37]

- The model has been tested against many metrics that most microbe-enabled models will not be able to satisfy
- However, further testing is clearly warranted

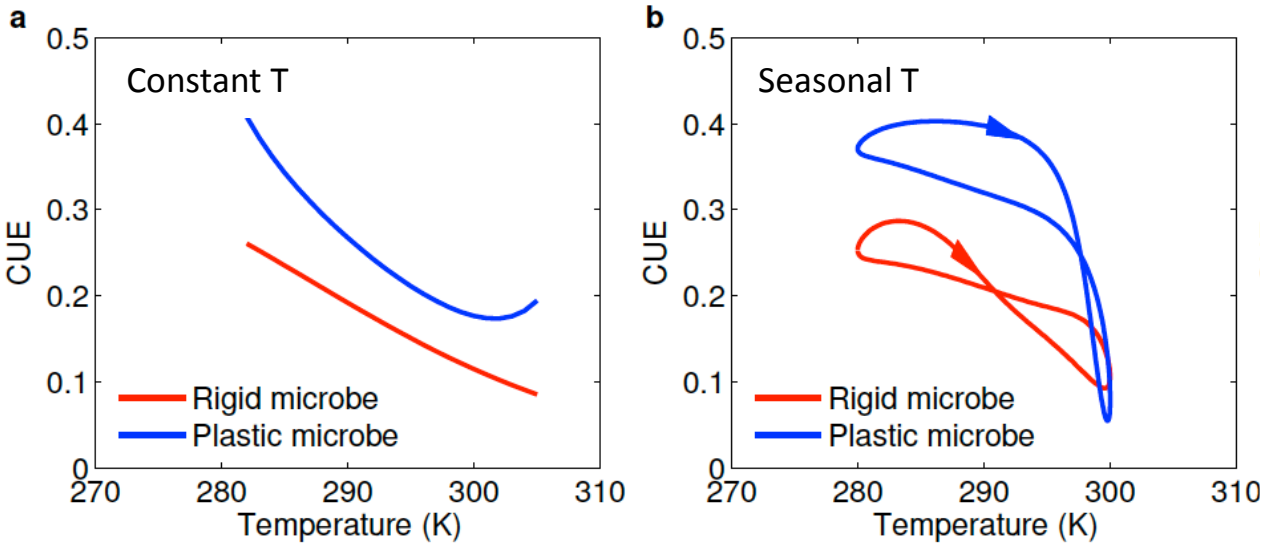
Tang and Riley, 2014, *Nature CC*

CUE Predictions



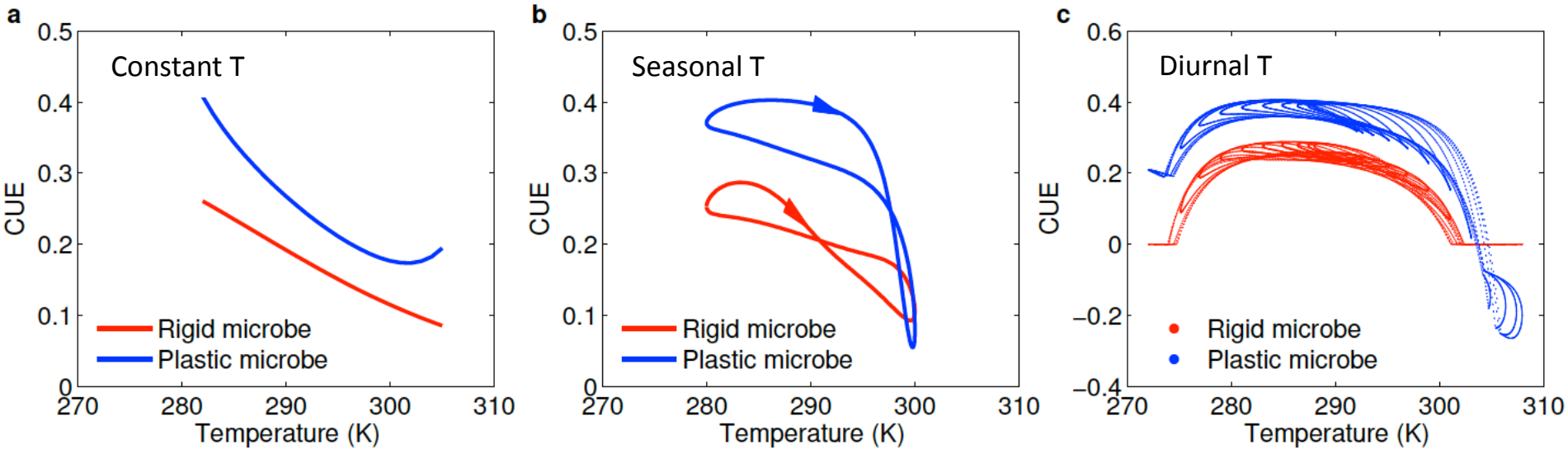
- For constant temperature, CUE dependence appears consistent with current formulations used in land BGC models
- However, …

CUE Predictions



- Seasonal cycle forcing gives different emergent responses for rigid and plastic microbes
- And …

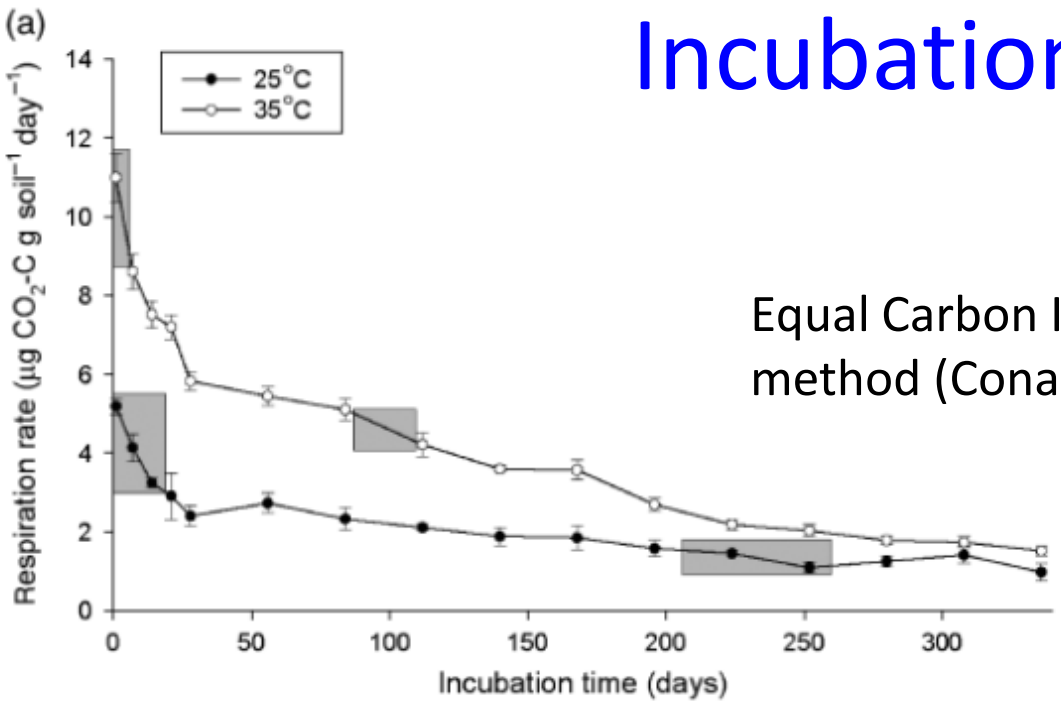
Highly Variable CUE Precludes Direct Empirical CUE Parameterization



- Hourly variation gives very different functional form
- There are insufficient empirical data to fully characterize CUE temperature dependence variability

Tang and Riley, 2014, *Nature CC*

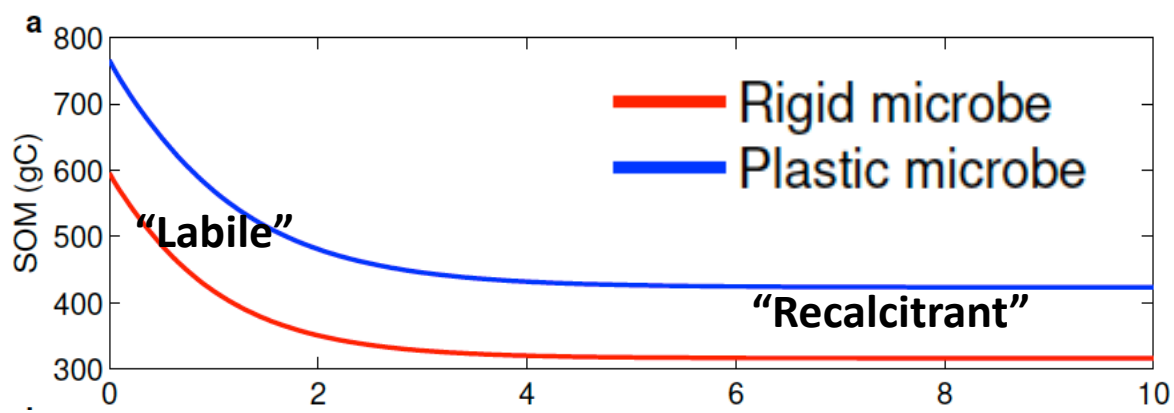
Interpreting "Recalcitrance" from Incubations



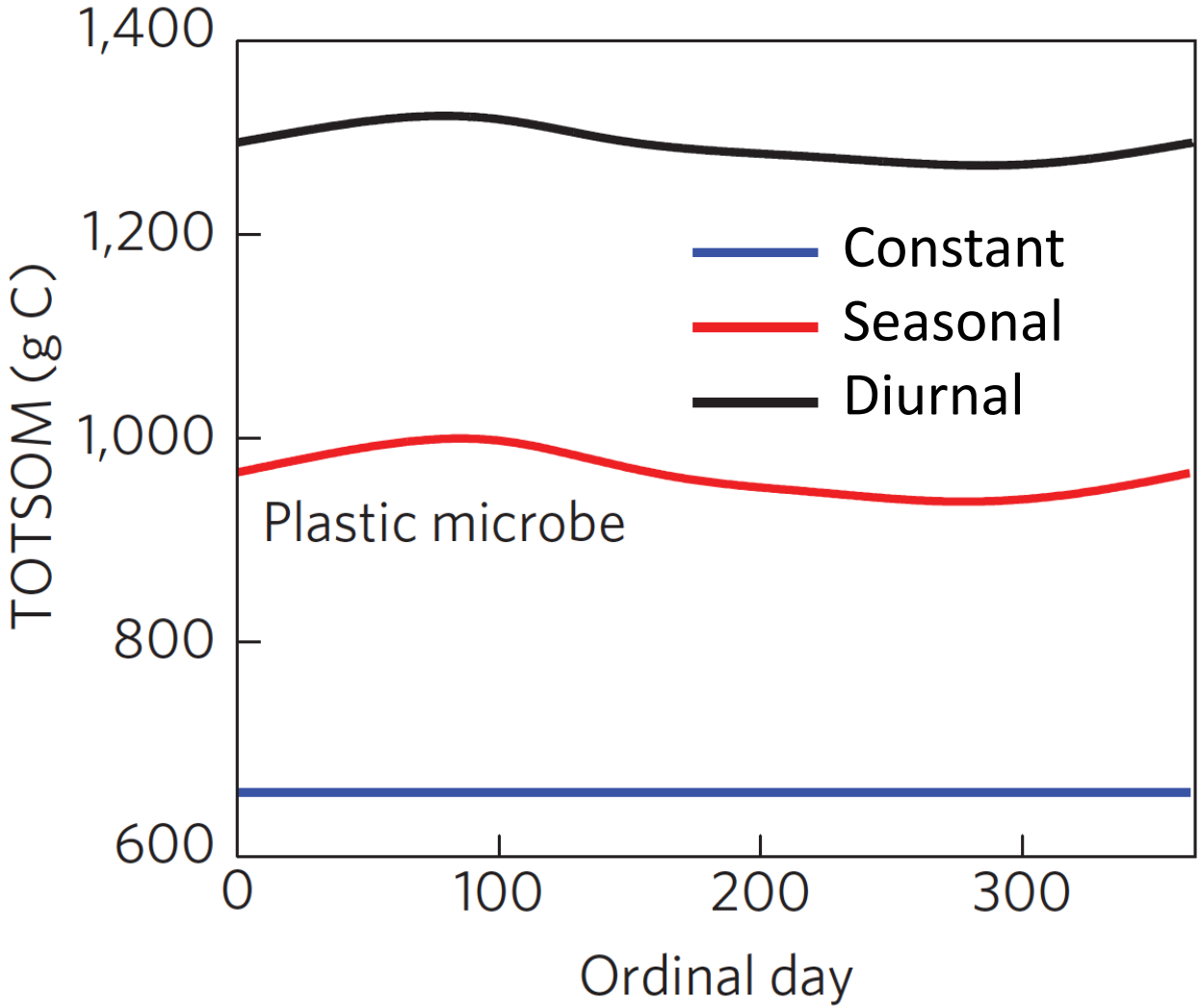
Equal Carbon Incubation method (Conant et al., 2008)

Predictions with only one substrate, one microbe, and abiotic interactions have

- Same functional form
- Very different interpretation



Impacts



Tang and Riley, 2014, *Nature CC*

Summary

- Observations suggest highly variable Q_{10} and CUE
- Our model with microbes, mineral surfaces, and process-specific temperature sensitivities:
  - Is consistent with observed temperature sensitivity dynamics
  - Highlights deficiencies in interpreting and applying laboratory incubations in land BGC models
    - Q_{10} and CUE temperature sensitivity are emergent dynamic properties, not static functions
  - Leads to smaller predictions of temperature change impacts on SOM stocks
- MODEX implications
  - Falsifying the hypotheses presented here requires high temporal resolution incubations with measurements of
    - Substrates
    - Microbial community activity and structure
    - Exoenzymes

NGEE-Arctic Literature Discussed

Bouskill, N. J., Tang, J., Riley, W. J., and Brodie, E. L.: Trait-based representation of biological nitrification: model development, testing, and predicted community composition, Frontiers in Microbiology, 3, 1-17, doi: 10.3389/fmicb.2012.00364, 2012.

Bouskill, N. J., Riley, W. J., and Tang, J. Y.: Meta-analysis of high-latitude nitrogen-addition and warming studies imply crucial ecological mechanisms overlooked by land models, in press Biogeosciences, 2014.

Ghimire, B., Riley, W. J., and Koven, C. D.: Improved representation of global leaf and root physiology, and its role in carbon and nitrogen cycling in the Community Land Model, submitted Biogeosciences, 2014a.

Ghimire, B., Riley, W. J., Koven, C. D., Kattge, J., Rogers, A., Reich, P., and Wright, I.: Leaf nitrogen allocation for integration with terrestrial land models, in prep Global Change Biology, 2014b.

Koven, C. D., Lawrence, D. M., and Riley, W. J.: Permafrost-carbon feedback: Sensitivity to deep soil decomposability and the nitrogen cycle, submitted Proceedings National Academy of Sciences, 2014.

Maggi, F., and Riley, W. J.: The effect of temperature on the rate, affinity, and 15N fractionation of nitrate during biological denitrification in soils, submitted Biogeosciences, 2014.

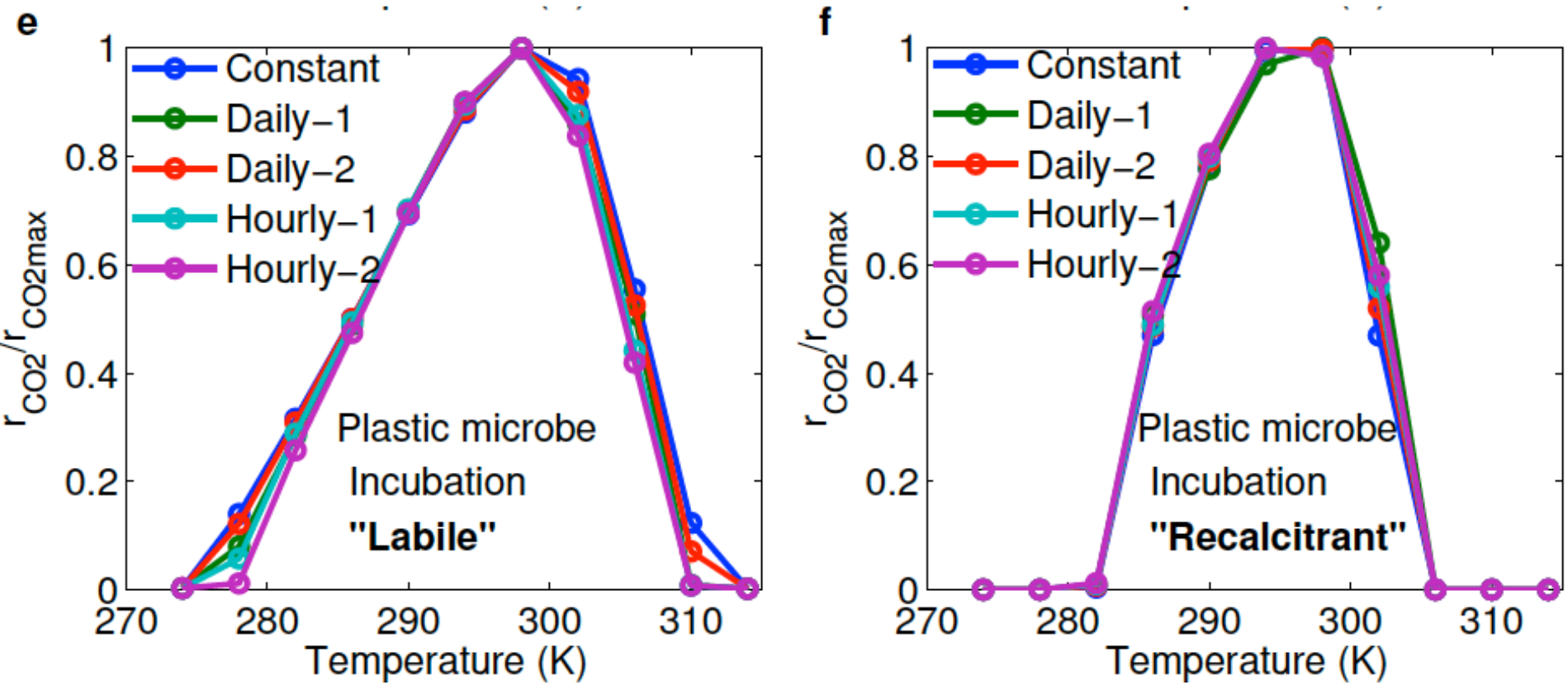
Mishra, U., and Riley, W. J.: Scaling impacts on environmental controls and spatial heterogeneity of soil organic carbon stocks, submitted Biogeosciences, 2014.

Riley, W. J., Maggi, F. M., Kleber, M., Torn, M. S., Tang, J. Y., Dwivedi, D., and Guerry, N.: Long residence times of rapidly decomposable soil organic matter: Application of a multi-phase, multi-component, and vertically-resolved model (BAMS1) to soil carbon dynamics, Geoscientific Model Development, 7, 1335-1355, doi:10.5194/gmd-7-1335-2014, 2014.

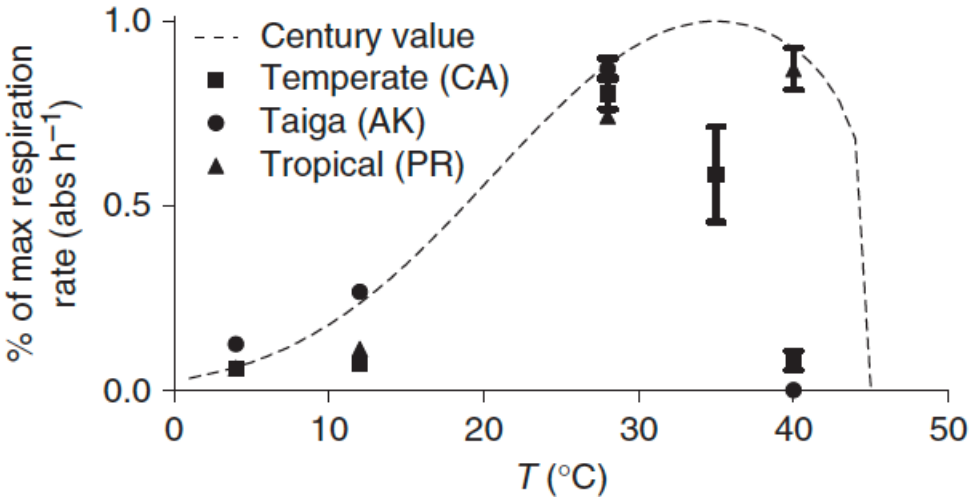
Tang, J. Y., and Riley, W. J.: A total quasi-steady-state formulation of substrate uptake kinetics in complex networks and an example application to microbial litter decomposition, Biogeosciences, 10, 8329-8351, Doi 10.5194/Bg-10-8329-2013, 2013.

Tang, J. Y., and Riley, W. J.: Weaker carbon-climate feedbacks resulting from microbial and abiotic interactions, Nature Climate Change, DOI: 10.1038/NCLIMATE2438, 2014a.

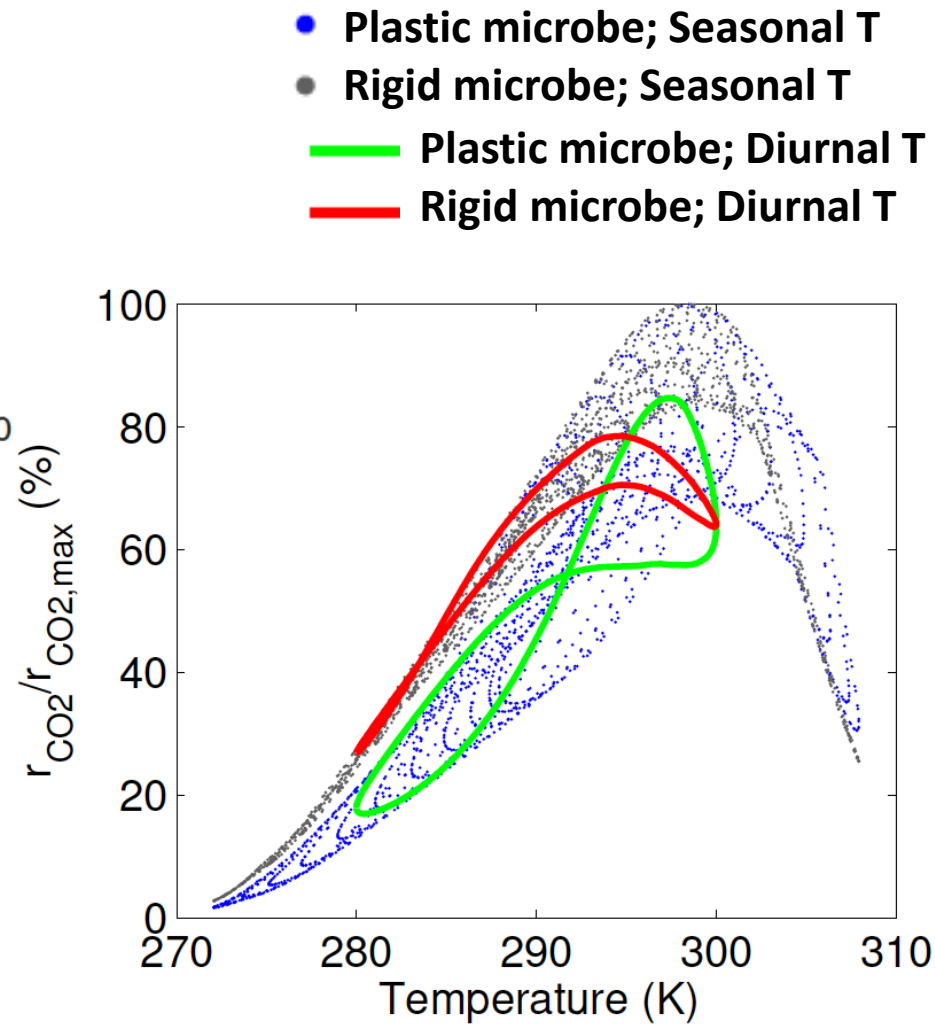
Emergent respiration temperature sensitivity



Incubations May Confound Multiple Controllers of Temperature Sensitivity



Balser and Wixon, 2009



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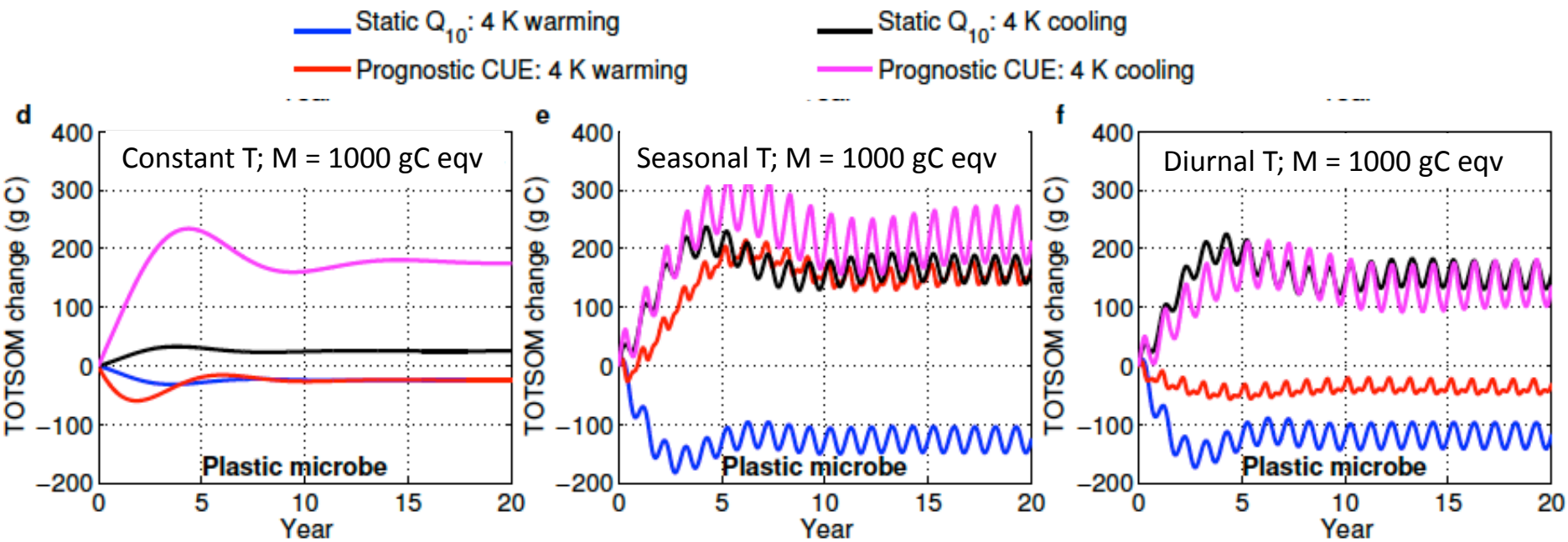
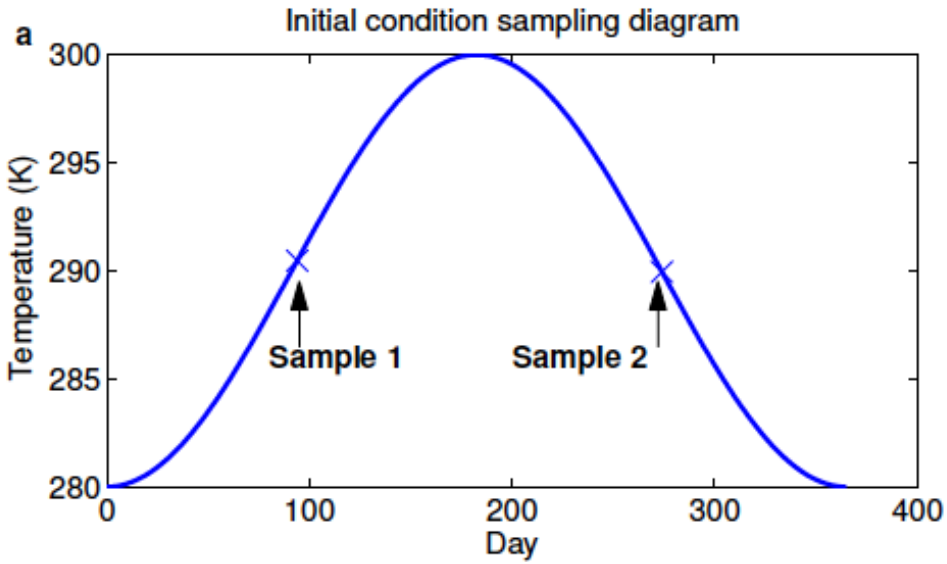
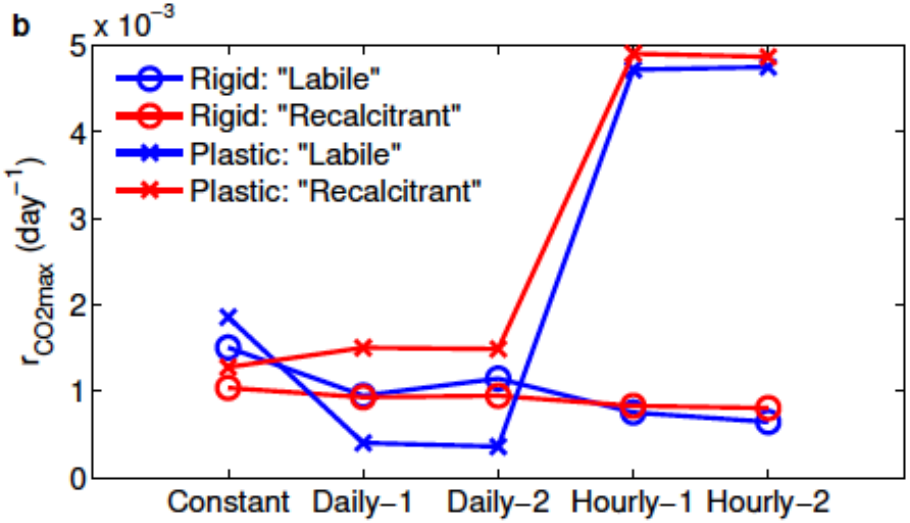
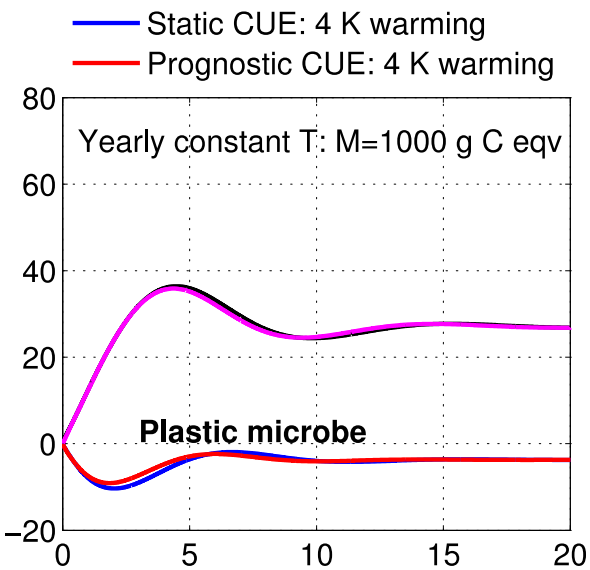

Static Q_{10}: 4 K warming
Prognostic CUE: 4 K warming
Static Q_{10}: 4 K cooling
Prognostic CUE: 4 K cooling
d
e
f
Constant T; M = 1000 gC eqv
Seasonal T; M = 1000 gC eqv
Diurnal T; M = 1000 gC eqv
Plastic microbe
TOTSOM change (g C)
Year
400
300
200
100
0
−100
−200
0
5
10
15
20

Intrinsic decomposability depends on sampling time





CUE Impacts



y constant T: M=2000 g C eqv

Plastic microbe

- Uncertainty in SOM predictions result from:
  - Incorrect temporal forcing and averaging of respiration and temperature
  - Misinterpretation of mineral surface interactions
  - Ignoring microbial plasticity