

Exploring the Ameriflux Data

Trends and Relationships

Igor Markelov

Upscaling Group Meeting

June 16, 2017

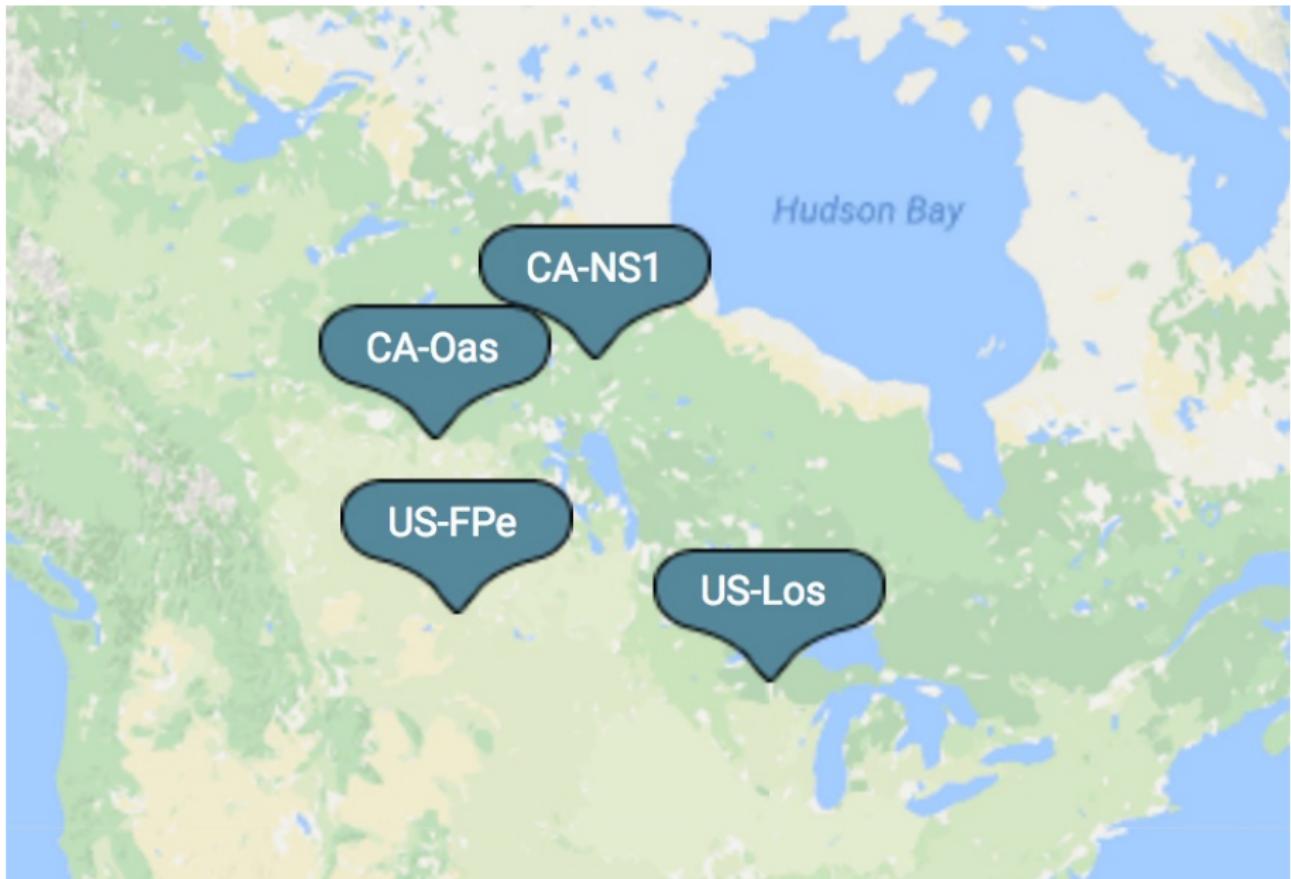
Sites

Name	Climate	Type	Mean T, C	Mean P, mm
CA-NS1	Dfc	ENF	-2.89	500.29
CA-NS6	Dfc	OSH	-3.08	495.37
CA-Oas	Dfc	DBF	0.34	428.53
US-FPe	Bsk	GRA	5.48	334.8
US-Los	Dfb	WET	4.08	828

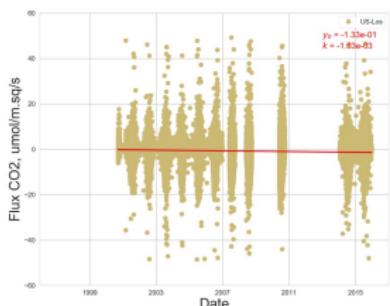
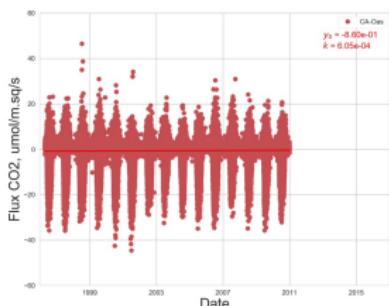
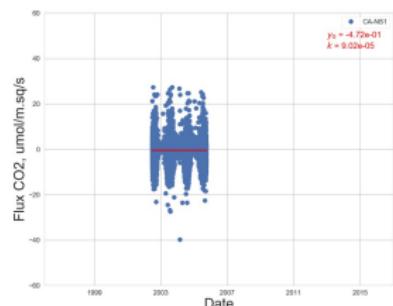
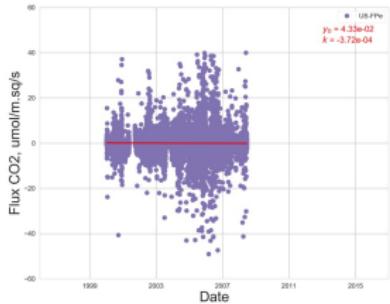
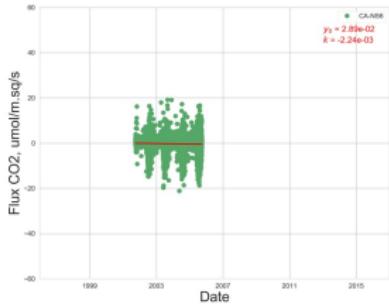
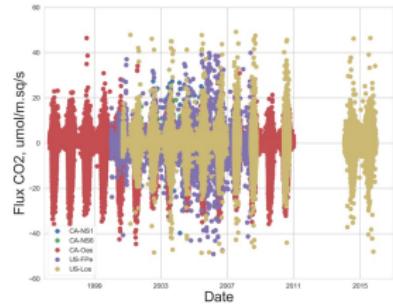
Climate: Dfc - Subarctic: severe winter, no dry season, cool summer; Bsk - Cold semi-arid climate, steppe, warm winter; Dfb - Warm Summer Continental: significant precipitation in all seasons.

Vegetation: ENF - Evergreen Needleleaf Forests; OSH - Open Shrublands; DBF - Deciduous Broadleaf Forests; GRA - grassland; WET - Permanent Wetlands.

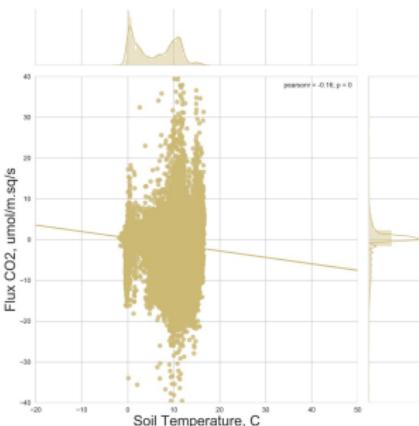
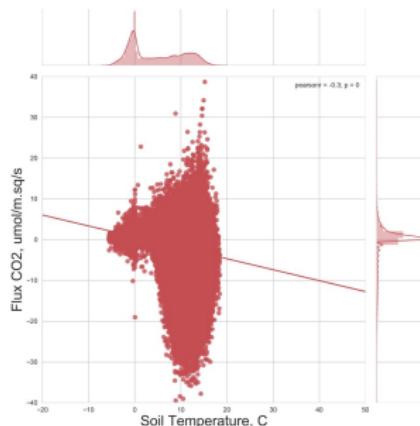
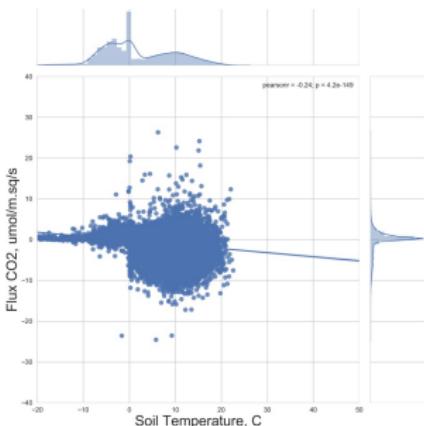
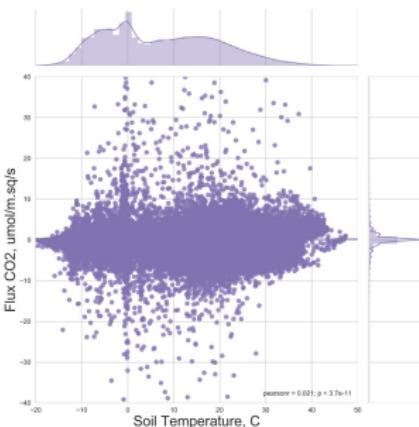
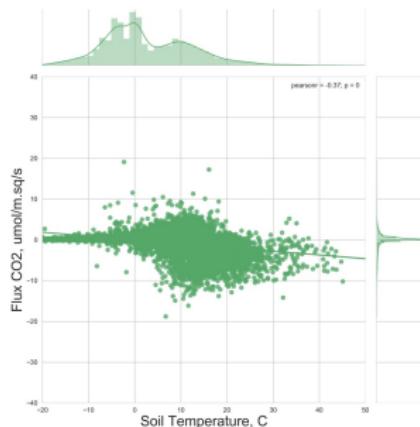
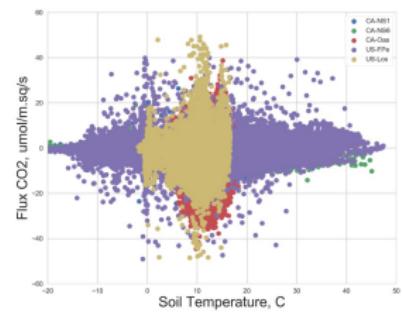
Sites



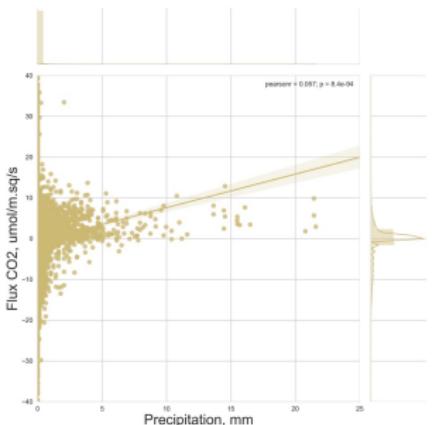
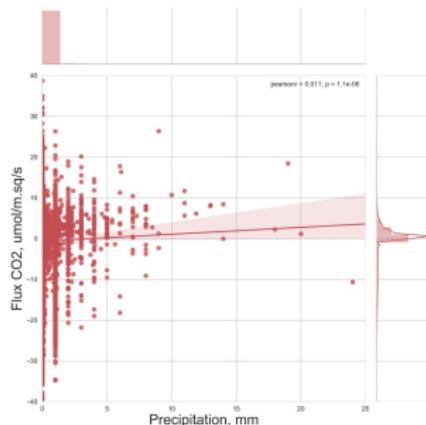
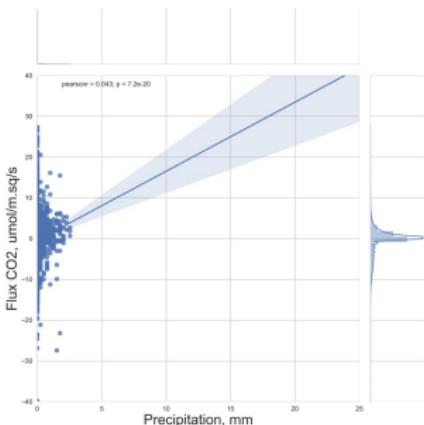
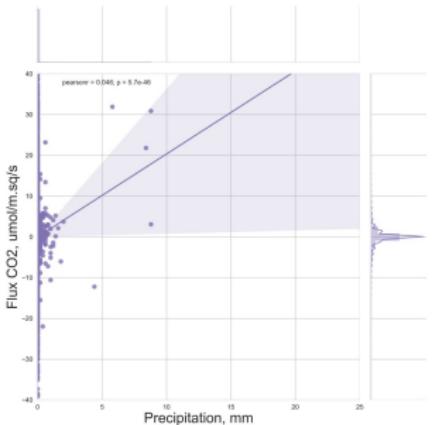
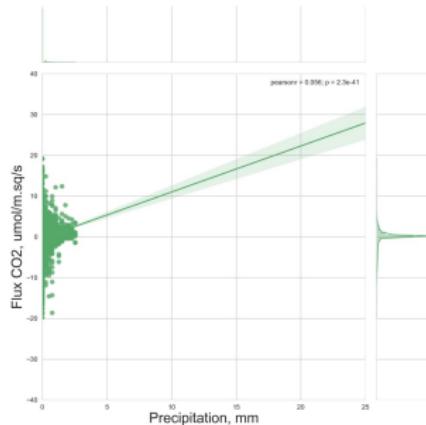
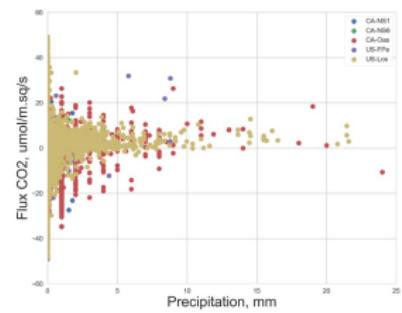
Flux in Time



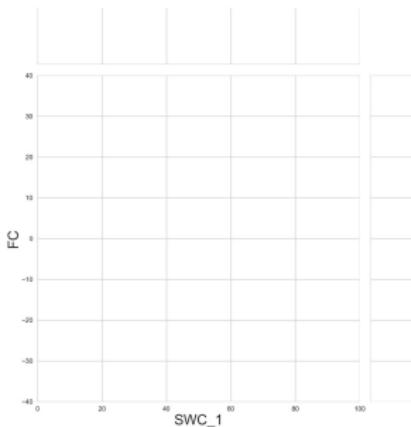
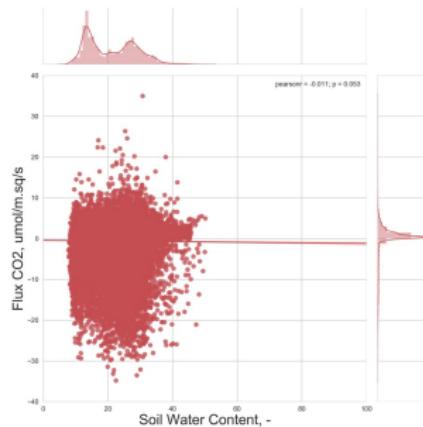
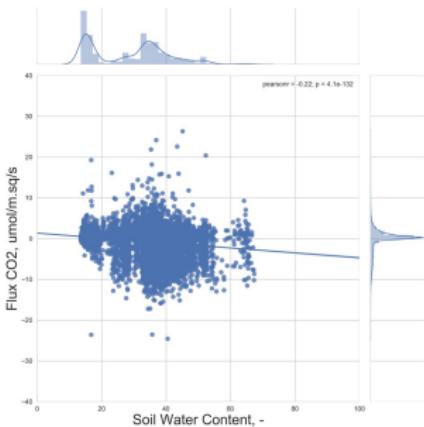
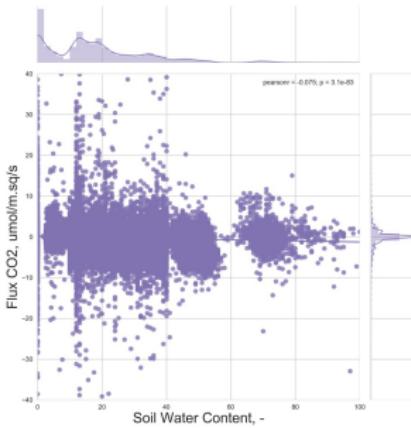
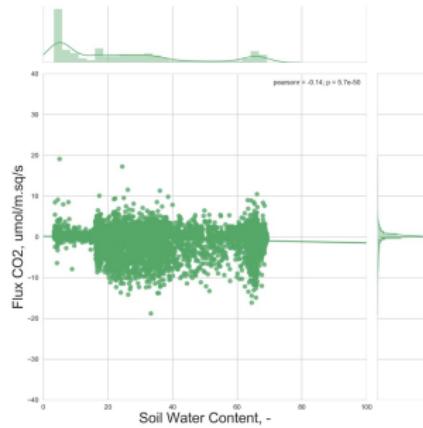
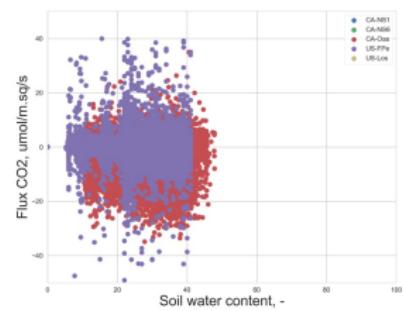
Flux vs Soil Temperature



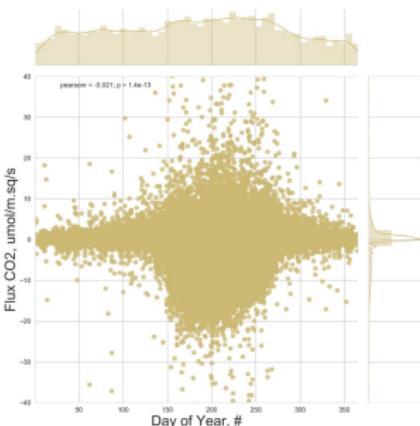
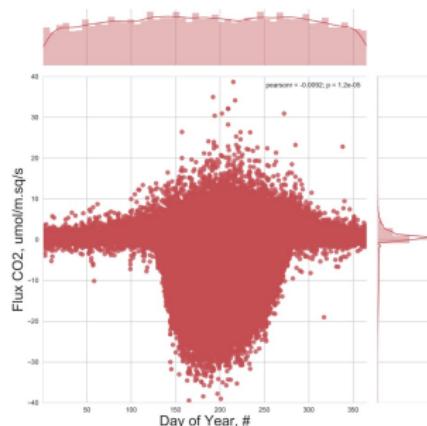
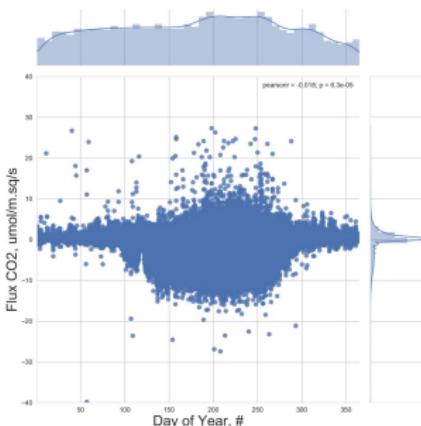
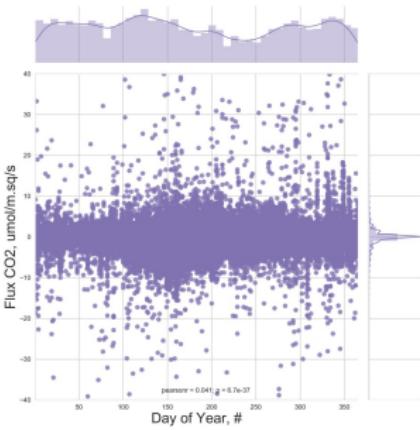
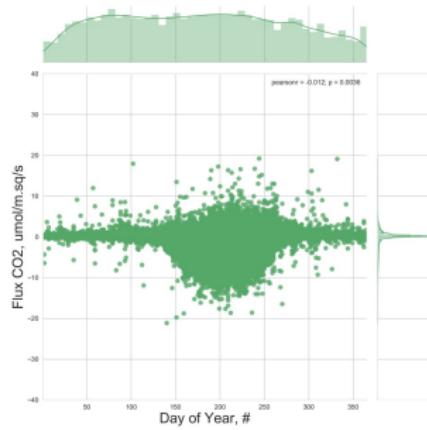
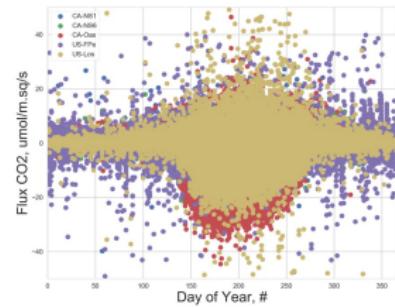
Flux vs Precipitation



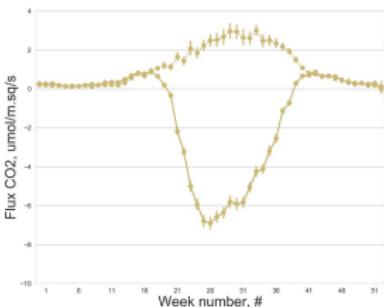
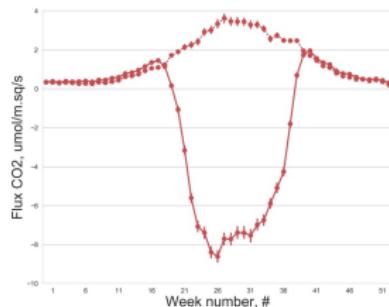
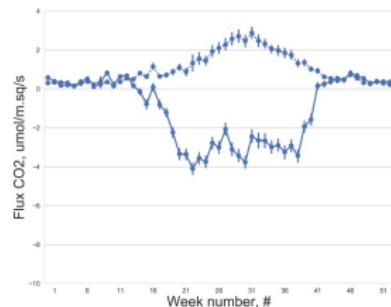
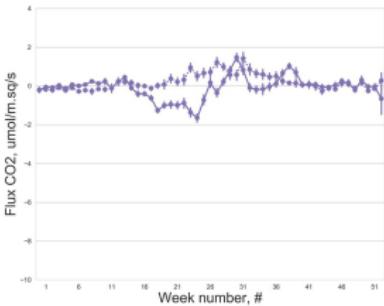
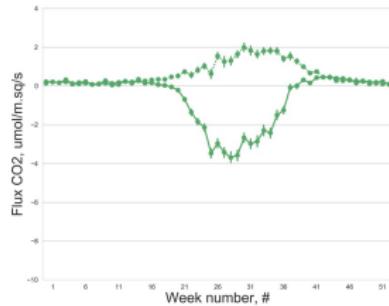
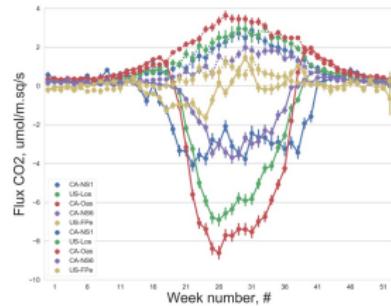
Flux vs Soil Water Content



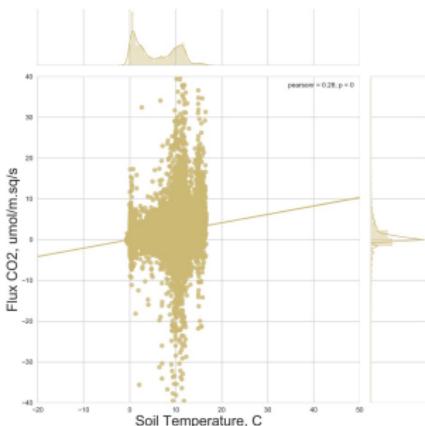
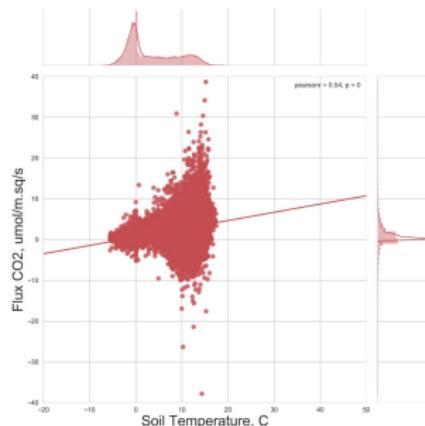
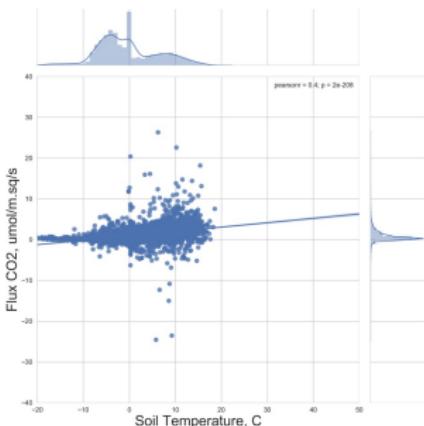
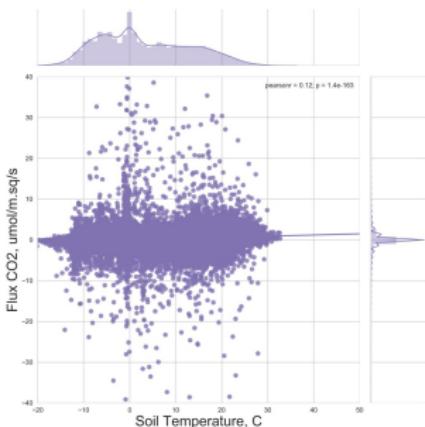
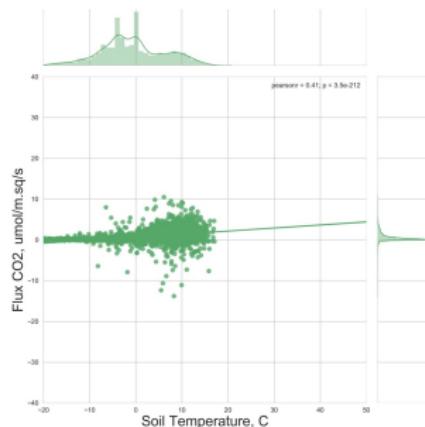
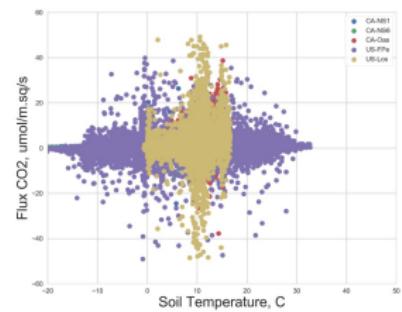
Flux on Yearly scale



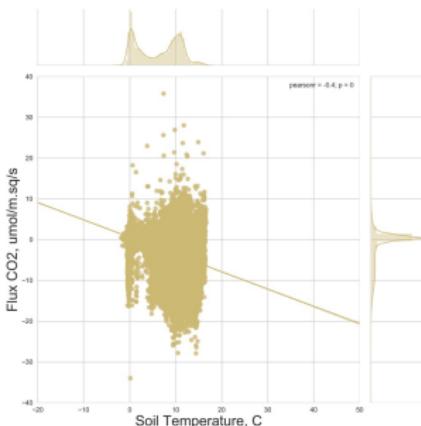
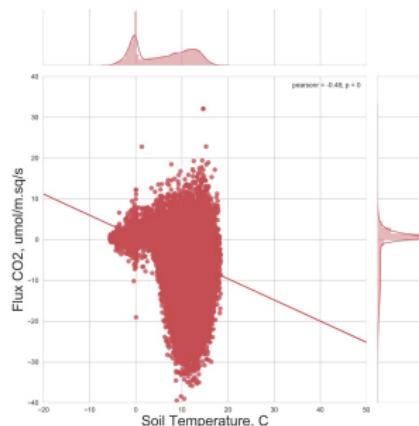
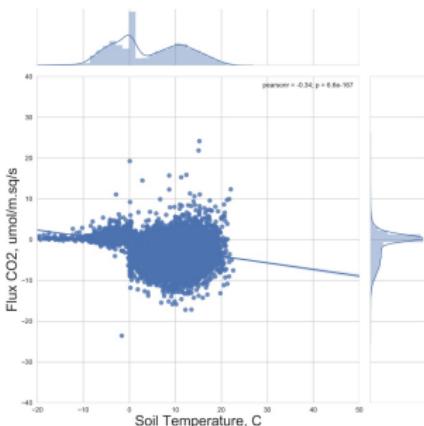
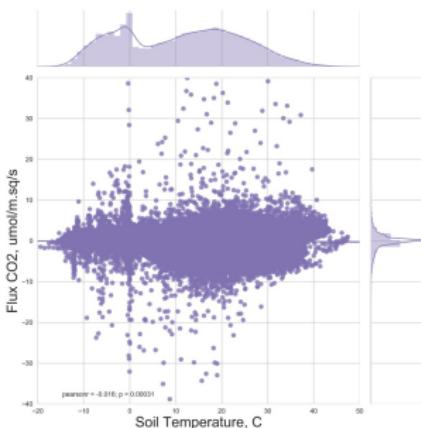
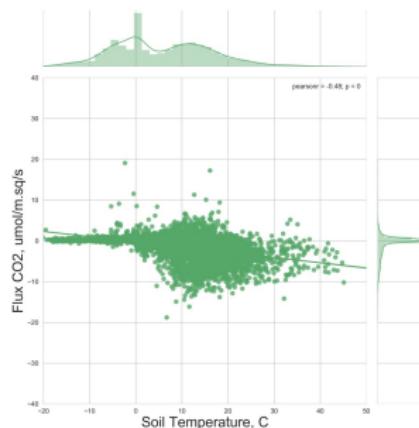
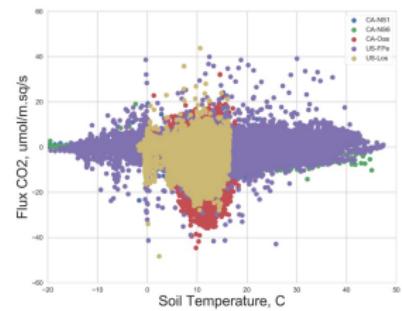
Weekly average: Day/Night



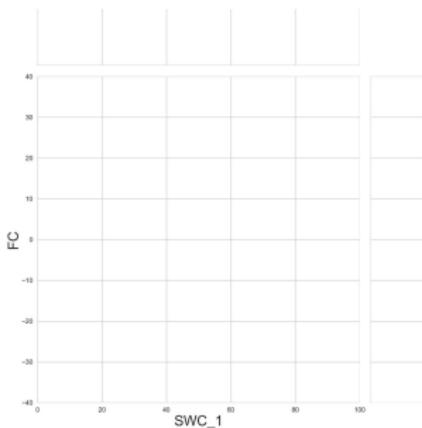
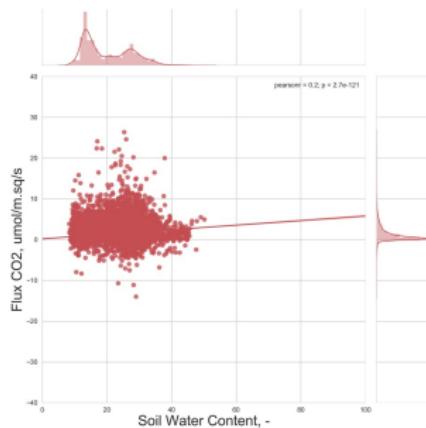
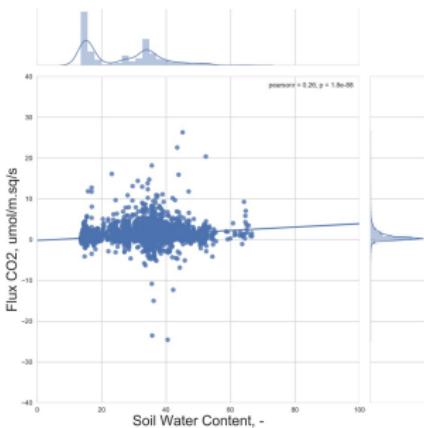
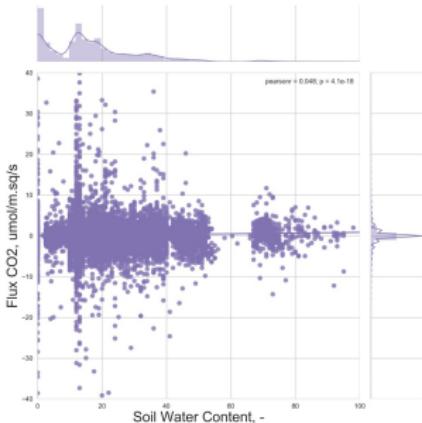
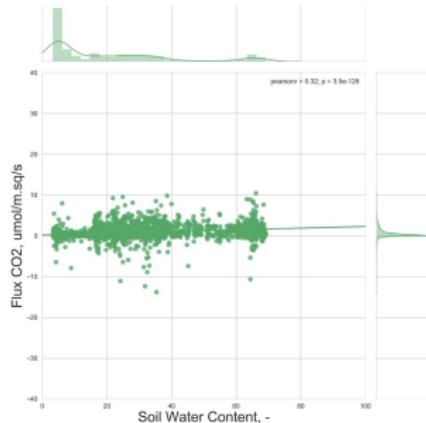
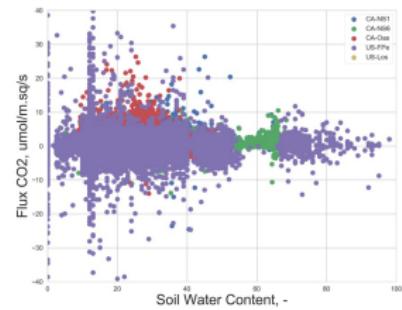
Flux vs Temperature at Night



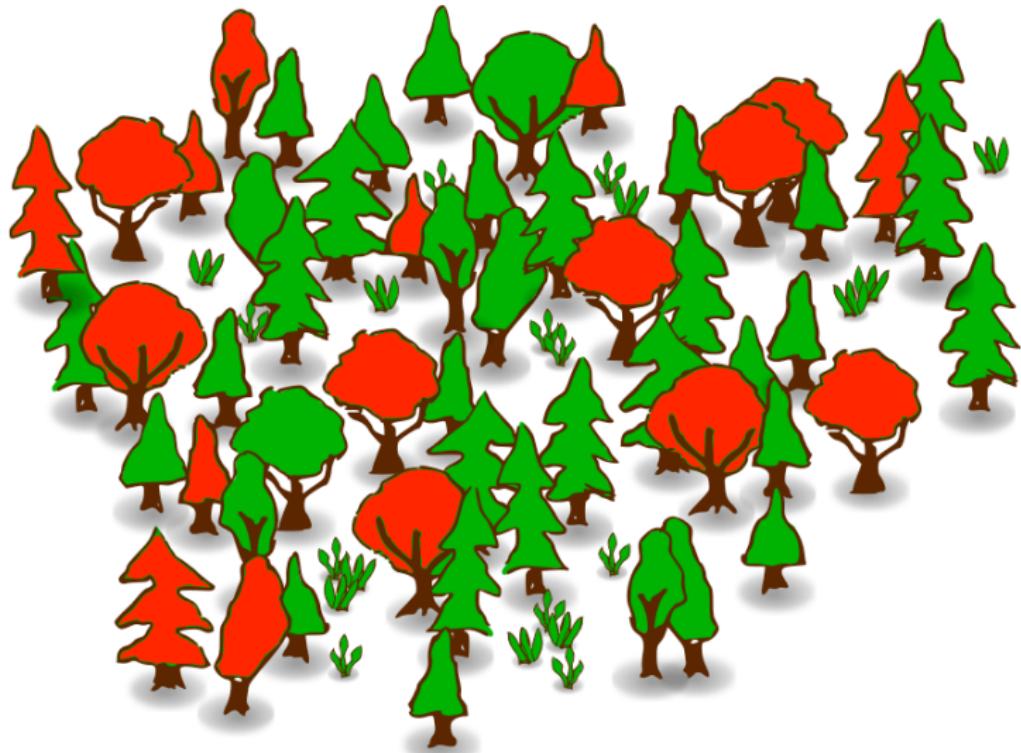
Flux vs Temperature during Daylight



Flux vs Soil Water Content at Night

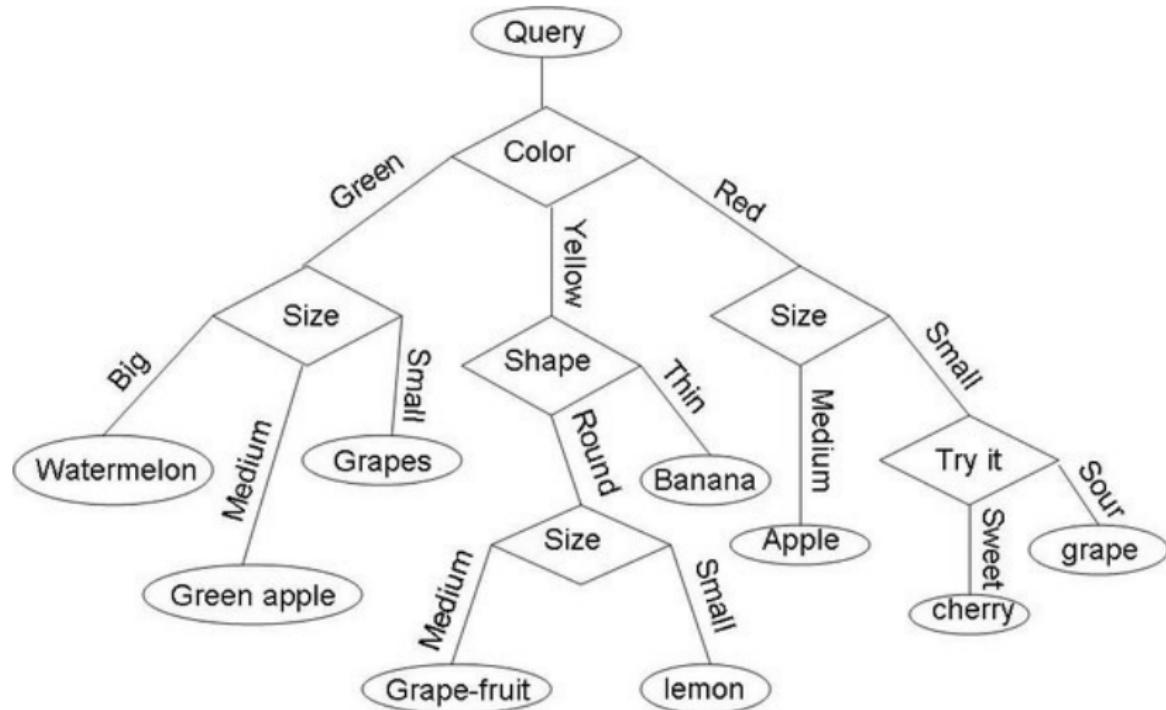


Machine Learning: Random Forests¹



¹Breiman, L. *Machine Learning* (2001) 45:5. doi:10.1023/A:1010933404324.

Machine Learning: Random Forests

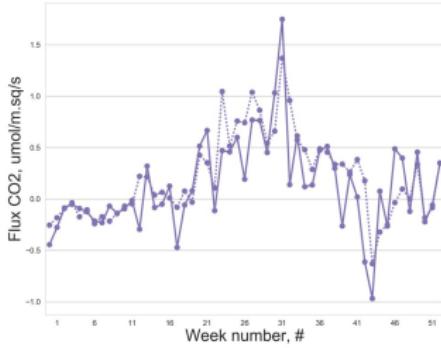
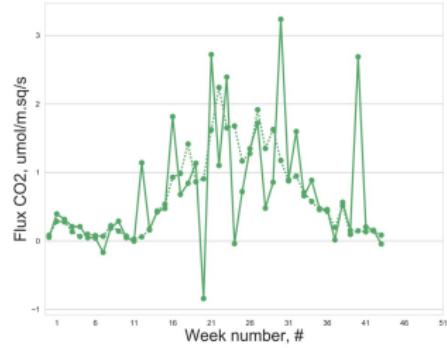
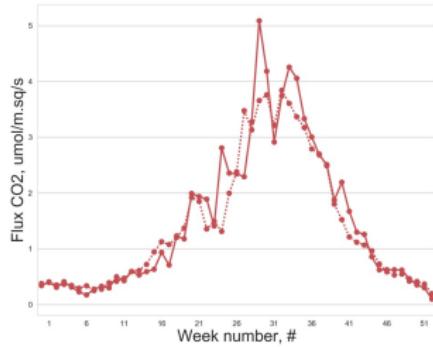
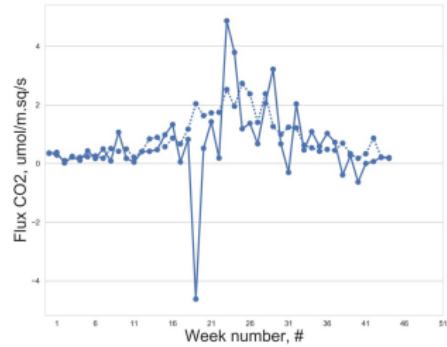


Random Forests Algorithm: Predicted vs Measured (Night)

Features: SWC, T, P, Lat, Long, Date

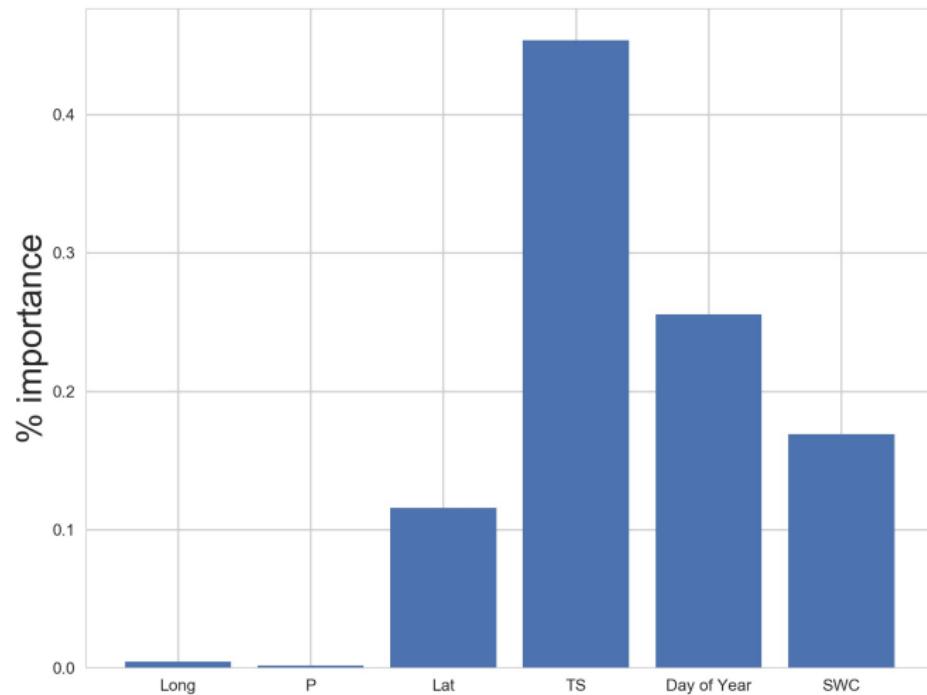
Random Forests Algorithm: Predicted vs Measured (Night)

Features: SWC, T, P, Lat, Long, Date



Random Forests Algorithm

Relative Importance of Features



Train on all data (25 Sites). Six Modeled Sites

Modeled Sites:

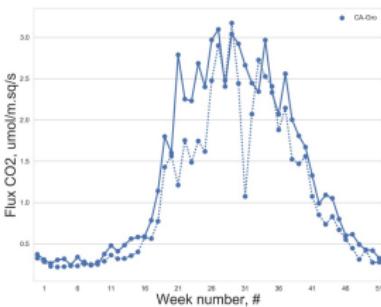
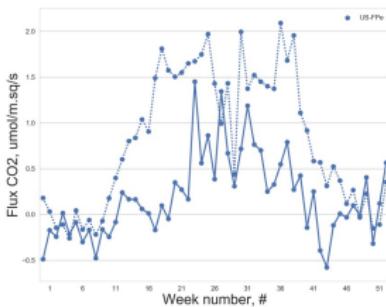
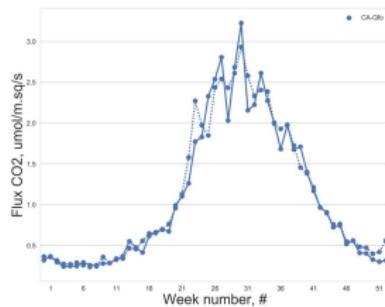
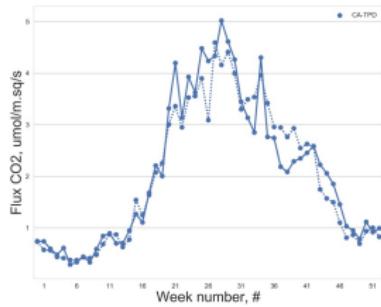
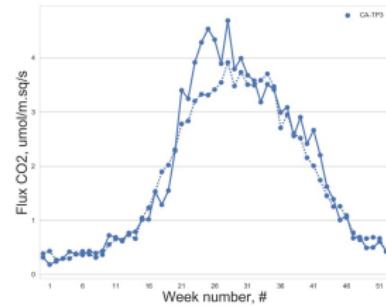
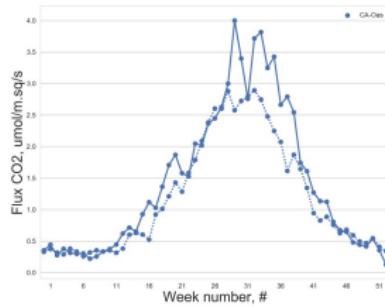
Station	Climate	Type	Mean T, C	Mean P, mm	Elev., m
CA-OAS	Dfc	DBF	0.34	428	530
CA-Qfo	Dfc	ENF	-0.36	962	382
CA-TP3	Dfb	ENF	8	1036	184
US-Fpe	Bsk	GRA	5.48	335	634
CA-TPD	Bsk	GRA	8	1036	260
CA-GRO	Dfb	MF	1.3	831	340

Climate: Dfc - Subarctic: severe winter, no dry season, cool summer; Bsk - Cold semi-arid climate, steppe, warm winter; Dfb - Warm Summer Continental: significant precipitation in all seasons.

Vegetation: ENF - Evergreen Needleleaf Forests; DBF - Deciduous Broadleaf Forests; GRA - grassland; MF - mixed forest;

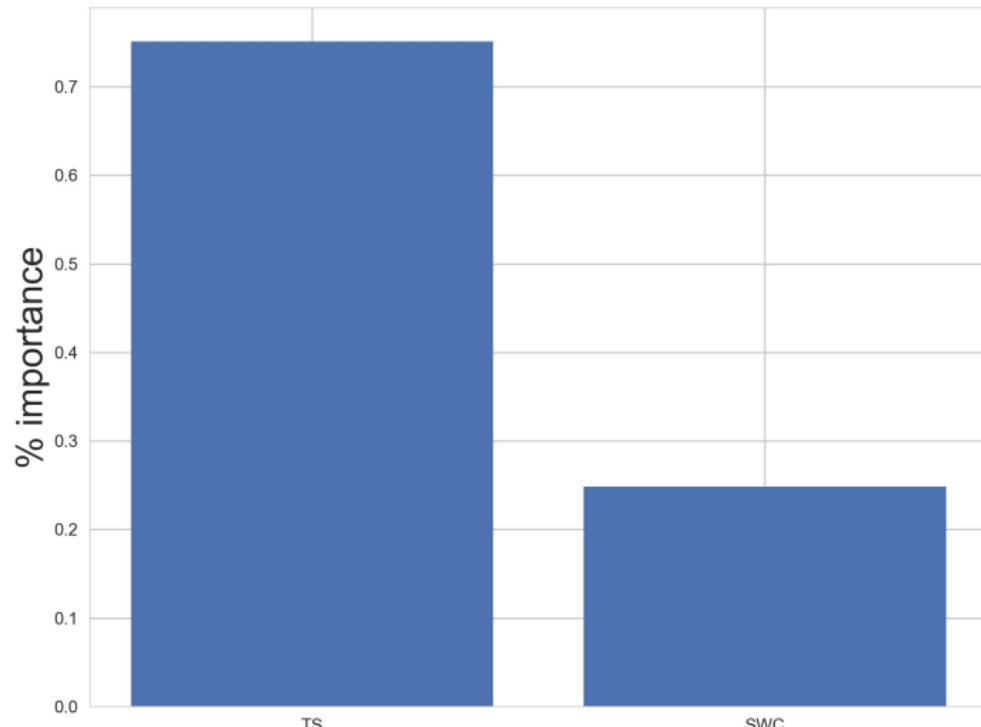
Random Forests Algorithm: Predicted vs Measured (Night)

Features: SWC, T; Train on all data



Random Forests Algorithm: Train on all data (25 Sites)

Relative Importance of Features

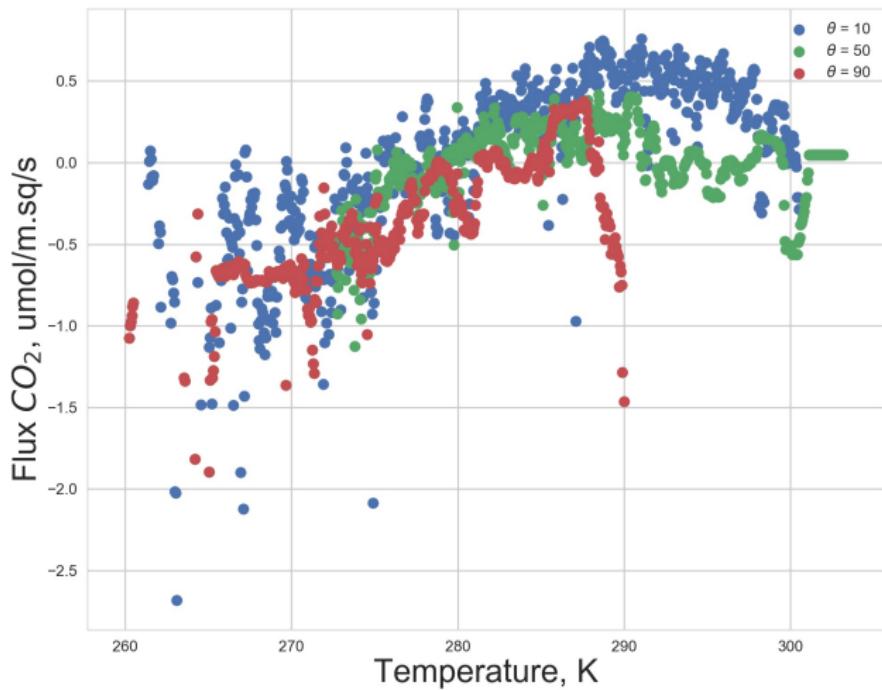


Reverse Engineering of Random Forests Algorithm

$T = [-10; +30]$ with $\Delta T = 0.001$
 $\theta = [0; 1]$ with $\Delta \theta = 0.001$
 10^6 combinations

Reverse Engineering of Random Forests Algorithm

T dependence (Night)



Reverse Engineering of Random Forests Algorithm

T dependence (Night)

Modified Arrhenius equation for optimum T:

$$\frac{F}{F_{max}} = \frac{\exp \left[\frac{-E_a}{RT_0} \left(1 - \frac{T_0}{T} \right) \right]}{1 + \exp \left[\frac{ST - H_d}{RT} \right]} \quad (1)$$

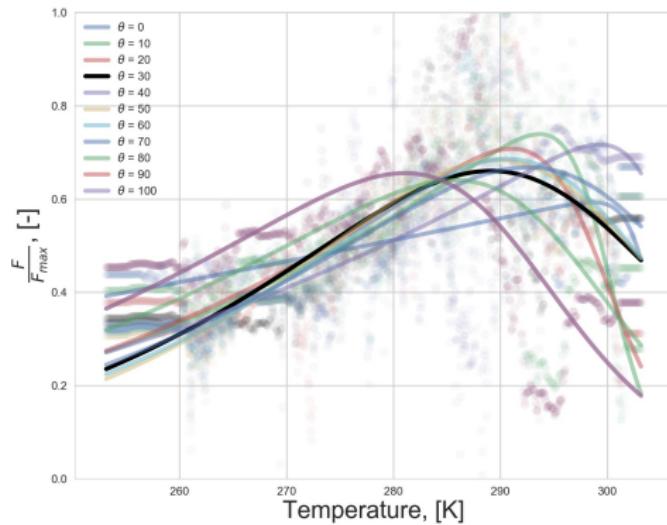
Fitting params:

$$T_0 = 293.4 \text{ K} \quad (2)$$

$$E_a = -22.1 \text{ kJ/mol} \quad (3)$$

$$S = 304.1 \text{ J/mol/K} \quad (4)$$

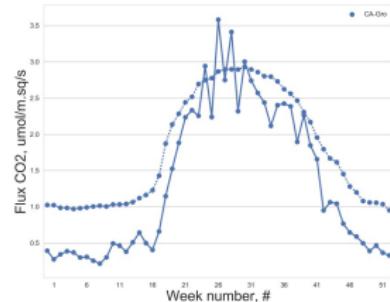
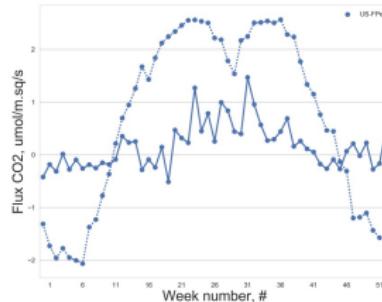
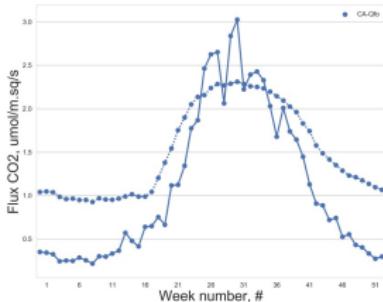
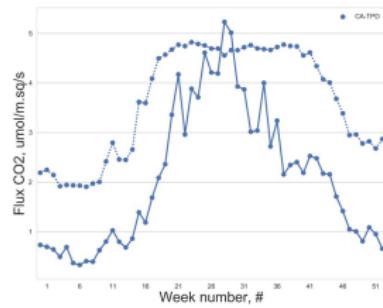
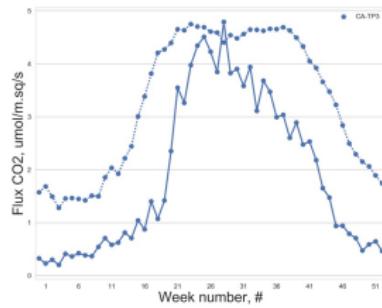
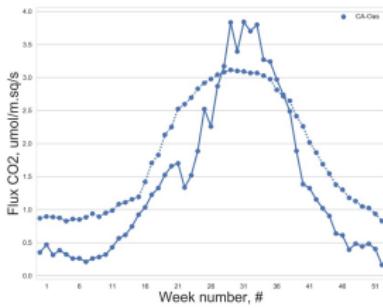
$$H_d = 90.6 \text{ kJ/mol} \quad (5)$$



Reverse Engineering: Predicted (eq. 6) vs Measured

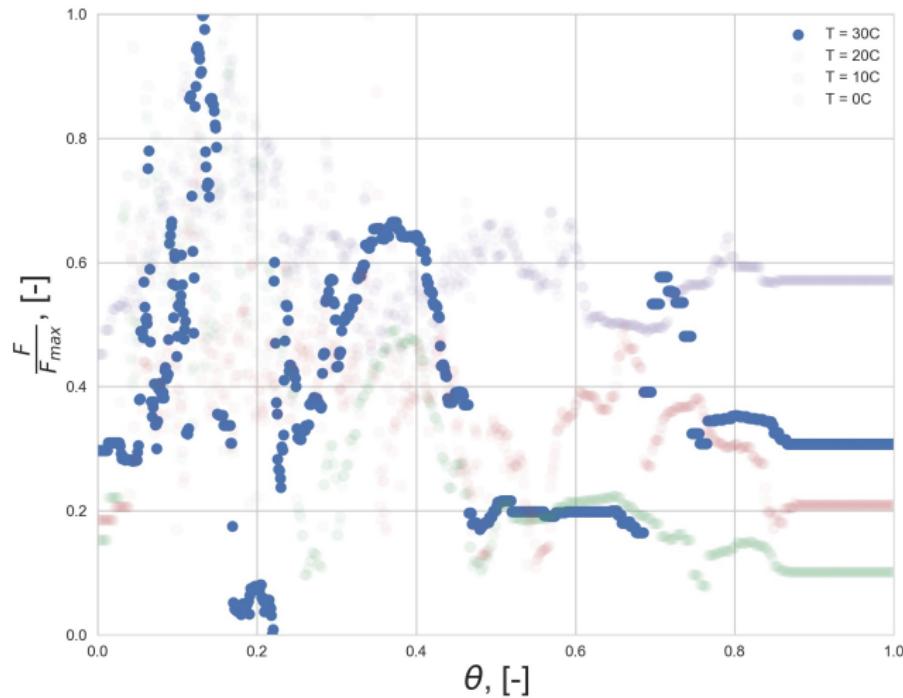
Measured - solid line; eq. 6 - dashed line

$$F = F_{max} \cdot f(T) \quad (6)$$



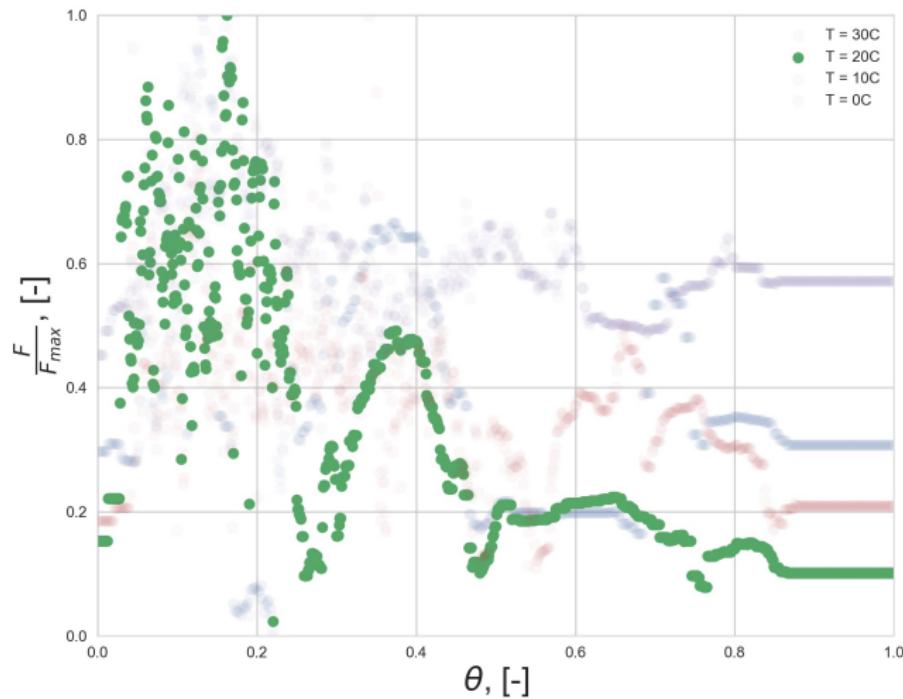
Reverse Engineering of Random Forests Algorithm

θ dependence (Night)



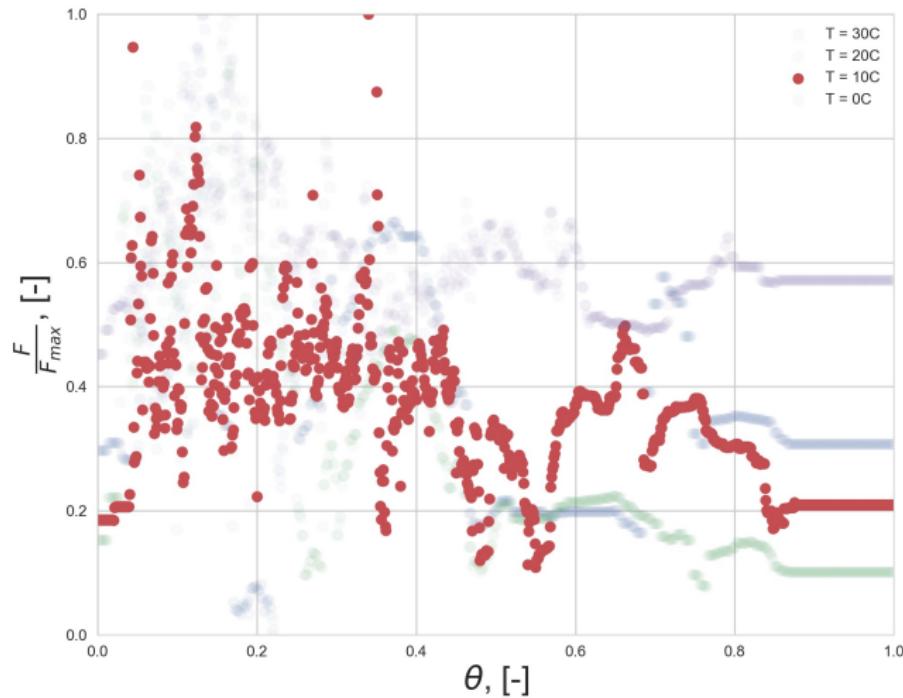
Reverse Engineering of Random Forests Algorithm

θ dependence (Night)



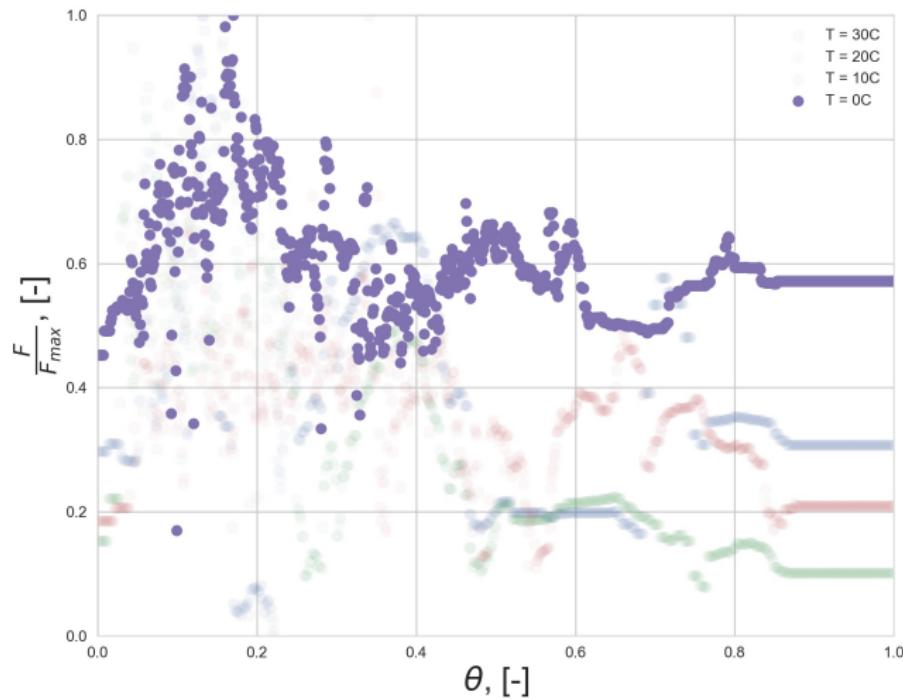
Reverse Engineering of Random Forests Algorithm

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Reverse Engineering of Random Forests Algorithm

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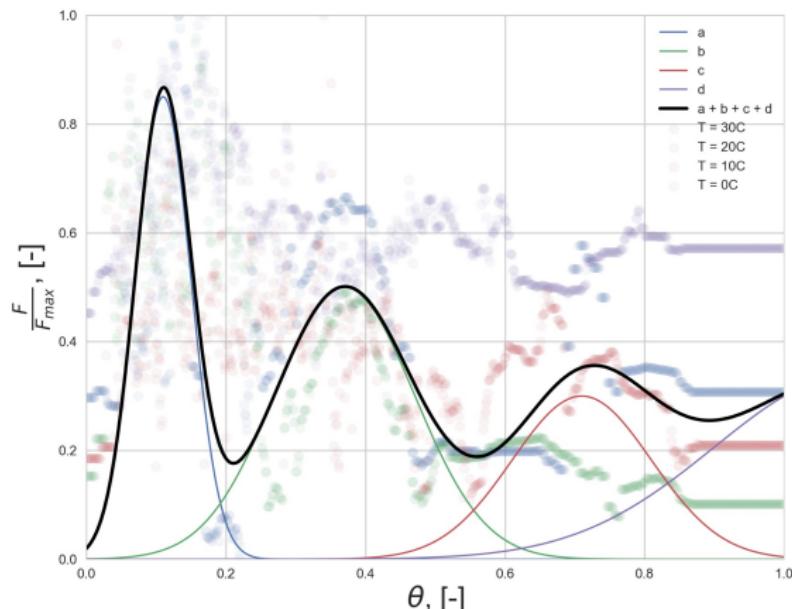
Reverse Engineering of Random Forests Algorithm

θ dependence (Night)

$$\frac{F}{F_{max}} = \sum_i^4 A_i \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(x-\mu_i)^2}{2\sigma_i^2}} \quad (7)$$

Fitting params:

Parameter	a	b	c	d
A	0.85	0.5	0.5	0.3
μ	0.11	0.37	0.71	1.1
σ	0.04	0.1	0.1	0.2



Reverse Engineering: Predicted (eq. 8) vs Measured

Measured - solid line; eq. 8 - dashed line

$$F = 0.75F_{max} \cdot f(T) + 0.25F_{max} \cdot f(\theta) \quad (8)$$

