Posterior Simulation

We simulated the posterior distribution of G_S using an error distributed as $N(0, \sigma_{(js)}^2)$ in a discrete time state-space framework at a 30-minute time step. This is then scaled by the stomatal time constant (τ). If we let $V_{\tau(js)} = 1 - \exp(-dt/\tau_{(js)})$ and tN(w,x,y,z) indicate a truncated normal distribution with mean w and variance x, constrained to the interval [y,z], we then have G_S distributed as

$$G_{S(jst)} \sim tN\left(G_{S(js(t-1))} + \left(G_{SS(jst)} - G_{S(js(t-1))}\right)V_{\tau(js)}, \sigma_{(js)}{}^2 V_{\tau(js)}, 0, G_{MAX(t)}\right) \quad \text{(S1)},$$

where we set $G_{MAX(t)}$ at a value above the expected range of observed values for either species (400 mmol m^{-2} s^{-1}) during the daytime and 25 mmol m^{-2} s^{-1} during nighttime, somewhat higher than the 15 mmol m^{-2} s^{-1} estimated using eddy-covariance techniques at this site (Lai et al. 2000; Novick et al. 2009b). In addition to this process-level error, we estimated a measurement error distributed as N(0, $\rho_{(js)}^2$), so that J_S at sensor i is distributed as

$$J_{S(jstdi)} \sim N\left(\overline{J_{S(jst)}}\phi_{(jstdi)}, \rho_{(js)}{}^2\right) \quad \text{(S2)},$$

where $\overline{J_{S(jst)}}$ is the mean sap flux at time t across the sapwood area of the species s in treatment j.

We simulated the posterior distributions of all parameters conditional on the data, model structure above and priors in a Gibbs sampling framework. We simulated the posterior of $G_{S(jst)}$ in a state-space framework by sequentially updating the value at each time step t conditional on the previous and subsequent time steps (Clark 2007). This method only draws on data where it is present, with uncertainty increasing with the proportion of missing data and lengths of gaps without data (Clark et al. 2011). Once the time-series of $G_{S(jst)}$ was determined, the time series of $\overline{J_{S(jst)}}$ was calculated using a simple hydraulic model. For *P. taeda*, a calibration value of the hydraulic time constant (κ = 64.5 min) was estimated from analysis of 2009 data on sensors at two heights in the stem (Ward et al. in review). This value was then multiplied by the ratio of treatment height in the model period to 2009 height across treatments, resulting in time constants that ranged from 39.6 to 66.0 minutes. *L. styraciflua* was assumed to have negligible hydraulic time constant at the half-hourly time step. Hydraulic time constants in similar sized individuals of another diffuse porous broadleaf (*Betula lenta*) were on the order of 5-10 minutes (Daley et al. 2008).

We then sampled the parameters $G_{SRef(js)}$ and $\lambda_{(js)}$ by a single Metropolis within Gibbs step, using only data above 0.20 $M_{(jt)}$ to minimize tradeoffs with $f_{M(jst)}$, due to the collinearity of $D_{(t)}$ and $M_{(jt)}$ over longer time periods (weeks to months). Parameters for $f_{M(jst)}$ and $f_{Q(jst)}$ were also sampled by a single Metropolis step each. For all parameters in $f_{D(jst)}$, $f_{M(jst)}$ and $f_{Q(jst)}$, data were restricted to above 0.6 kPa $D_{(t)}$ to avoid errors arising from uncertainty in $D_{(t)}$ measurements (Ewers and Oren 2000) and the jump distributions were adaptive (Gelman 2004), updated every 40 iterations for a target acceptance rate of 0.13 to 0.30. Random effects ($\overline{\phi_{(jstd)}}$) were sampled directly based on the data for each sensor and $\overline{J_{S(jst)}}$ with a prior distribution of $N(1,\omega_{(js)})$, then constrained by dividing by the sum on the RHS of Eq. 6. The variance parameters ($\sigma_{(js)}^2$, $\rho_{(js)}^2$ and $\omega_{(js)}^2$) were sampled directly from their posteriors conditional on the other parameters and the data, with an inverse gamma distribution with prior means of 5, 1 and 1, respectively, and the prior weight scaling with the number of measurements in the sample period. The Gibbs sampler was run for 15000 iterations and we simulated posteriors distributions from samples taken from the last 10000 iterations, with the first 5000 steps discarded as a burn in period. Visual inspection of posterior chains estimated that most parameters converged within a few hundred steps and all within 3000 steps.

A Gibbs sampling Markov Chain Monte Carlo algorithm (Gelfand and Smith 1990) was used to simulate posterior distributions. A complete description of this algorithm, including diagnostics and convergence analyses is given in Bell (2011). Details specific to this simulation are given in Supplementary Material. To account for phenological changes in the evergreen canopy (McCarthy et al. 2007; McCarthy et al. 2006), we independently simulated posteriors of the data for *P. taeda* for 3 overlapping intervals per year, corresponding to day-of-year (DOY) intervals (0,146), (110,256) and (219,365) or (219,366) in leap years. These intervals represent periods of low ('spring'), increasing ('growing season') and decreasing ('autumn') A_L, respectively. Simulated posteriors of $G_{S(ijt)}$ were summarized as means and standard deviation of half-hourly values for the Gibbs sampler output for each model period. Overlapping periods were included to check for consistency in $G_{S(ijt)}$ estimates between periods and avoid large step changes in phenology. Values for the overlapping intervals were taken as the average of the posterior bounds and means. For *L. styraciflua*, each year of data was simulated independently, using the period with active leaf area, which varied between years. Priors and hyperparameters for all fit parameters are given in the Supplementary Material (Table S2), as well as the mean and standard deviation of posterior values across years for each treatment for each model period (Table S3).

Table S1. The number of sap flux sensors by treatment, year and species. F indicates fertilized plots and C indicates control plots.

Year	**Depth**	**Ambient CO_2**				**Elevated CO_2**			
	mm	*P. taeda*		*L. styraciflua*		*P. taeda*		*L. styraciflua*	
		C	**F**	**C**	**F**	**C**	**F**	**C**	**F**
1998	0-2	40		12		49		12	
	20-40	6				6			
1999-	0-20	35	5	12		38	11	12	
2000	20-40	6		6		6		6	
2001-	0-20	39	15	17	5	39	15	17	5
2004	20-40	17	5	6		17	5	6	
	40-60	11	5			11	5		
2005-	0-20	25	30	15	7	25	29	11	11
2007	20-40	9	12	5	1	13	13	2	4
	40-60	7	9			6	10		
2008	0-20	23	25	12	12	24	25	12	12
	20-40	9	17	5	4	12	10	4	3
	40-60	6	6			6	6		

Table S2. List of parameters prior distributions by species. *tN(w,x,y,z)* indicates a truncated normal distribution with mean *w* and variance *x,* constrained to the interval [*y,z*].

Parameter	**Units**	**Prior Distribution**	
		P. taeda	*L. styraciflua*
G_{SRef}	mmol m^{-2} s^{-1}	*tN*(110,6.25×10^4,10,250)	*tN*(85,4×10^4,10,250)
λ	log(kPa)$^{-1}$	*tN*(0.6,0.04,0.45,0.85)	
β^1	unitless	*tN*(0.95,0.01,0.8,0.99)	
β^2	mmol m^{-2} s^{-1}	*tN*(0.4,0.04,0.2,0.6)	
β^3	unitless	*tN*(0.2,0.16,0.02,0.4)	
β^4	unitless	*tN*(0.2,0.16,0.125,0.33)	
ϕ	unitless	*tN*(1,ω_{js}^2,0.25,4)	

Table S3. Mean parameter values from posterior chains for all model periods by treatment. Standard deviation is given in parentheses. Treatments: ambient CO_2-unfertilized (AC), elevated CO_2-unfertilized (EC), ambient CO_2-fertilized (AF) and elevated CO_2-fertilized (EF). Model periods: *P. taeda* (*P.t.*) in the spring (DOY <147), growing (DOY 110 to 256), and autumn seasons (DOY>218), as well as *L. styraciflua* (*L.s.*) in period of active leaf duration each year. Values for AC/EC are for 1998-2008 and AF/EF are for 2005-2008.

Parameter	**Treatment**	***P.t.* Spring**	***P.t.* Growing**	***P.t.* Autumn**	***L.s.***
G_{SRef}	AC	97.1 (15.1)	103.1 (17.7)	74.7 (12.2)	75.4 (40.8)
	EC	89.1 (20.6)	93.0 (22.6)	67.9 (20.5)	41.3 (13.6)
	AF	81.7 (6.8)	91.3 (10.7)	66.7 (9.4)	48.6 (10.8)
	EF	98.8 (7.4)	98.4 (13.6)	67.8 (9.0)	58.5 (56.5)
λ	AC	0.458 (0.017)	0.621 (0.046)	0.523 (0.065)	0.497 (0.085)
	EC	0.455 (0.009)	0.623 (0.056)	0.527 (0.070)	0.492 (0.060)
	AF	0.473 (0.037)	0.646 (0.040)	0.571 (0.079)	0.495 (0.067)
	EF	0.462 (0.015)	0.644 (0.042)	0.573 (0.074)	0.459 (0.015)
β^1	AC	0.868 (0.033)	0.926 (0.038)	0.863 (0.036)	0.915 (0.038)
	EC	0.891 (0.034)	0.948 (0.029)	0.884 (0.043)	0.909 (0.041)
	AF	0.877 (0.031)	0.934 (0.018)	0.856 (0.044)	0.922 (0.018)
	EF	0.900 (0.018)	0.942 (0.024)	0.867 (0.043)	0.926 (0.023)
β^2	AC	575.9 (52.0)	586.6 (25.5)	542.5 (71.3)	524.1 (101.9)
	EC	594.8 (10.0)	596.7 (6.5)	531.4 (68.3)	586.3 (38.5)
	AF	586.9 (14.3)	596.8 (4.9)	509.6 (79.2)	573.7 (44.4)
	EF	581.4 (31.1)	597.2 (4.3)	534.6 (60.7)	586.3 (23.2)
β^3	AC	0.120 (0.134)	0.094 (0.057)	0.059 (0.117)	0.118 (0.054)
	EC	0.149 (0.143)	0.101 (0.052)	0.104 (0.058)	0.140 (0.080)
	AF	0.097 (0.060)	0.081 (0.049)	0.100 (0.049)	0.163 (0.078)
	EF	0.069 (0.014)	0.082 (0.016)	0.085 (0.042)	0.125 (0.020)
β^4	AC	0.151 (0.058)	0.225 (0.033)	0.222 (0.043)	0.264 (0.055)
	EC	0.188 (0.033)	0.237 (0.025)	0.230 (0.057)	0.235 (0.061)
	AF	0.149 (0.036)	0.228 (0.035)	0.243 (0.052)	0.246 (0.085)
	EF	0.241 (0.033)	0.244 (0.012)	0.237 (0.054)	0.284 (0.051)
σ	AC	11.46 (4.68)	10.17 (5.46)	8.68 (6.59)	9.48 (5.44)
	EC	9.57 (3.91)	8.33 (4.62)	7.07 (4.17)	4.44 (1.68)
	AF	8.56 (3.99)	9.72 (6.00)	5.26 (2.67)	3.45 (0.48)
	EF	8.93 (4.04)	9.69 (6.96)	4.67 (1.72)	6.19 (6.03)
ρ	AC	1.79 (0.46)	2.29 (0.70)	1.70 (0.25)	2.57 (0.42)
	EC	1.83 (0.21)	2.19 (0.46)	1.84 (0.48)	2.42 (0.37)

	AF	1.73 (0.36)	1.97 (0.17)	1.73 (0.10)	2.45 (0.27)
	EF	1.95 (0.26)	1.91 (0.29)	1.58 (0.17)	2.25 (0.16)
ω	AC	0.918 (0.072)	0.912 (0.065)	0.923 (0.070)	0.850 (0.085)
	EC	0.945 (0.074)	0.943 (0.070)	0.972 (0.085)	0.858 (0.095)
	AF	0.953 (0.076)	0.942 (0.067)	0.969 (0.081)	0.836 (0.131)
	EF	0.925 (0.064)	0.902 (0.053)	0.914 (0.060)	0.878 (0.104)