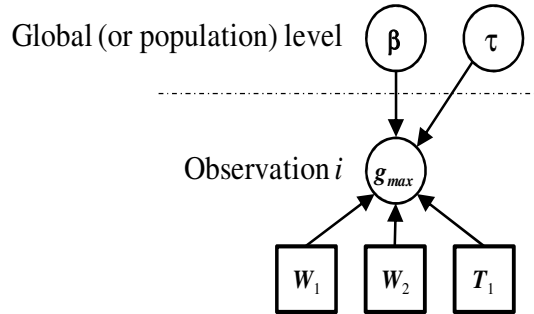


STOMATA EXAMPLE

In this project, you will gain experience implementing a Bayesian regression model and evaluating model fit. You are provided with data on maximum daily stomatal conductance (g_{max}) of a desert shrub. Plants are expected to regulate g_{max} such that they tend to close their stomata (reduce g_{max}) under water stress conditions (e.g., under low soil water content), and g_{max} may also be affected by air or leaf temperature. The data you are given include measurements of g_{max} , and associated covariates including “shallow” (0-30 cm soil depths) soil water (W_1), “deep” (30-60 cm) soil water (W_2), and nighttime temperature (T) preceding the daytime g_{max} measurement. Thus, for observation i ($i = 1, 2, \dots, 106$), you have $g_{max,i}$, $W_{1,i}$, $W_{2,i}$, and T_i . Based on plotting the data (which you might want to do yourself), you should log-transform g_{max} , which you will assume is normally distributed about a mean that is expressed as a regression model. You will conduct a linear regression of $\log(g_{max})$ on *covariate-centered* values of W_1 , W_2 , and T (call these W_{c1} , W_{c2} , and T_c), and you should include a quadratic effect for temperature (i.e., T_c^2) and all 2-way interactions involving W_{c1} , W_{c2} , and T_c (i.e., three 2-way interactions) and W_{c1} , W_{c2} , and T_c^2 (an additional two 2-way interactions since $W_{c1} \times W_{c2}$ will already have been included). Thus, the vector of regression coefficients (β) should contain 10 elements (intercept, 3 main effects, 1 quadratic effect for T_c , and 5 2-way interactions). The DAG for this model is given below (note: τ , the precision is a scalar). The g_{max} data are in units of moles $m^{-2} sec^{-1}$, W_1 and W_2 have units of cm^3 water / cm^3 soil, and T has unit of Celsius ($^{\circ}C$).

Level at which node varies:



The complete statistical model is as follows; for observation i and $y = \log(g_{max})$:

Likelihood: $y_i \sim Normal(\mu_i, \sigma^2)$

Mean model: $\mu_i = \beta_1 + \beta_2 W_{c1i} + \beta_3 W_{c2i} + \beta_4 T_{ci} + \beta_5 T_{ci}^2 + \beta_6 W_{c1i} W_{c2i} + \beta_7 W_{c1i} T_{ci} + \beta_8 W_{c2i} T_{ci} + \beta_9 W_{c1i} T_{ci}^2 + \beta_{10} W_{c2i} T_{ci}^2$

Where the centered covariates are defined as:

$$W_{c1i} = W_{1i} - \bar{W}_1, W_{c2i} = W_{2i} - \bar{W}_2, T_{ci} = T_i - \bar{T}$$

where \bar{W}_1, \bar{W}_2 , and \bar{T} are the corresponding sample means

Priors:

$\beta_k \sim Normal(0, 100000)$	conjugate, relatively non-informative
$k = 1, 2, \dots, 10$	(large variance [small precision])
$\tau \sim Gamma(0.1, 0.1)$	conjugate, relatively non-informative
	for precision ($\tau = 1/\sigma^2$)

Activities:

1. Program the model described above in JAGS by completing the “starter code” (Stomata_model_starter.R); if you get stuck, you can refer to the “solution code” (Stomata_model_SOLN.R). As part of this, include code for computing the standard deviation (σ) from the precision (τ), and for computing the covariate-centered covariates, W_{C1} , W_{C2} , and T_c (e.g., in R prior to providing the data to JAGS).
2. Since we are including a quadratic temperature effect (i.e., T_c^2), it is of interest to estimate the optimal temperature (T_{opt} , °C); i.e., T_{opt} is defined as the temperature that “yields” the maximum value of g_{max} that would be predicted at average values of W_1 and W_2 (i.e., at $W_{C1} = 0$ and $W_{C2} = 0$). Solve for T_{opt} (this should be a function of your regression coefficients, β), and include code in your JAGS model to compute T_{opt} so you can obtain its posterior statistics. NOTE: You will implement the regression model with *centered* temperature data, and you will need to compute T_{opt} on the “raw” / “non-centered” scale.
3. Specify starting values (initials) for 3 chains, for all root nodes. Initialize the JAGS model via `jags.model`, and use `coda.samples` to update the jags model and to monitor all parameters of interest (β , τ , σ , T_{opt} , deviance). Evaluate burn-in, mixing, convergence, and autocorrelation.
4. How many total iterations do you need to run to computer posterior statistics?
5. Produce posterior results from your above model, including posterior means and 95% CIs for the parameters of interest (i.e., β , τ , σ , and T_{opt}).
6. How would you evaluate model fit?
7. Interpret your posterior results with respect to the following.
 - a. How well did the model fit your data? Is the model biased in any way?
 - b. Which covariates seem to be important predictors of g_{max} ? For these “important” covariates, how do they affect g_{max} ? E.g., do your results support the hypothesis that water stress (lower soil water content) stimulates stomatal closure (reduces g_{max})? Is the response to soil water affected by nighttime temperature conditions?
 - c. How does nighttime temperature affect g_{max} , and what is the optimal temperature for g_{max} ?