(D)

$$\underbrace{P(U_x, U_y, g \mid R, h, g)}_{\text{Posterior}} = C\,\underbrace{P(U_x)P(U_y)P(g)}_{\text{Priors}}\;\overbrace{P(R,h,g \mid U_x, U_y, g)}^{P(\vec{R},h,g)}$$

If priors are constants, then:

$$P(U_x, U_y, g \mid R, h, g) = C'\,P(R,h,g \mid U_x, U_y, g)$$
$$= C'\,G(R, R_0, \sigma_R)\,G(h, h_0, \sigma_h)\,G(g, g_0, \sigma_g)$$

$\mu(U_y) = 4.34937$ $\sigma_{U_y} = 0.454$

$\mu(U_x) = 11.215$ $\sigma_{U_x} = 1.15$

Through Gauss fit to posterior distributions

These values are very close to the frequentist inferences, but are slightly larger than in (a) and slightly lower than in (b). This is presumably due to the lack of a Jacobian in the Bayesian inference. This makes the posterior distribution simply the product of 3 Gaussians. The distribution for U_y is skewed left while the distribution for U_x is skewed right.

(E) W/ logarithmic priors,

$$P(U_x, U_y, g \mid R, h, g) = C\,\frac{1}{U_x}\,\frac{1}{U_y}\,P(R,h,g \mid U_x, U_y, g)$$

$\mu(U_y) = 4.349$ $\sigma_{U_y} = 0.454$

$\mu(U_x) = 11.210$ $\sigma_{U_x} = 1.15$

Though I include the priors in the marginalization, the numbers barely change. I would expect the distribution to be weighted toward small values of U_x and U_y. The posterior distribution is no longer simply the sum of 3 Gaussians.

For a given U_x, the difference between constant & log priors is ~ 0.002. The μ-values are in fact skewed a bit toward smaller values of U_x and U_y.