Behavior model writeup

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Methods

To empirically parameterize homeowner-agent behavior, we conditioned a multi-level Bayesian statistical model on data from 637 homeowner survey respondents. We then use the model to generate new households drawn from the distribution implied by the model. The outcome variable of the model is the number of defensible space practices adopted by each homeowner, which we instantiate as a binomially distributed process. The model contains varying intercepts at the level of town (α_{town}), which allows the model to pool information across towns in determining the base adoption rate and models the effect of social forces on homeowner behavior. Experience with fire is included as a predictor as the natural logarithm of the distance of the home from recent fires (D). Three additional predictors were constructed from survey responses to charactarize the psychological makeup of homeowners: policy beliefs (P), beliefs about the effectiveness of defensible space practices (E), and beliefs about risk associated with wildfire (R). We employed weakly regularizing priors ($\mathcal{N}(0,1)$) for all four continuous predictors to reign-in overfitting. The model takes the form:

$$
\begin{aligned}
N_i &\sim binomial(4, p_i) \\
logit(p_i) &= \alpha_{town[i]} + \beta_P P + \beta_E E + \beta_R R + \beta_D ln(D) \\
\alpha_{town} &\sim Normal(\alpha, \sigma_{town}) \\
\alpha &\sim Normal(0, 5, 1) \\
\beta_P &\sim Normal(0, 1) \\
\beta_E &\sim Normal(0, 1) \\
\beta_R &\sim Normal(0, 1) \\
\beta_D &\sim Normal(0, 1) \\
\sigma_{town} &\sim HalfCauchy(0, 2).
\end{aligned}
$$

All analyses were performed in R version 3.3.1 (R Core Team 2016). For statistical modeling, we used the rethinking package (McElreath 2015) which samples posterior distributions using Hamiltonian Monte Carlo via Stan (Stan Development Team 2015). The full reproducability suite of data and code are available in a repository at XXX (xxx.com).

Bayesian models are generative, and we now describe how we can use the model to generate new agent-households. For any set of predictor values, there is an implied distribution of defensible space behaviors. This distribution is generated by drawing (1,000) samples of parameter values from the model's joint posterior distribution, multiplying the vectors of paramter values by a vector of predictor values to obtain a distribution of p values, which are then used in binomial trials to generate a distribution of number of defensible space behaviors. Note the two levels of stochasticity in this process: 1 in drawing parameters from the joint posterior distribution and another in the binomial trials for each p. This preserves uncertainty around defensible space behavior. There is a large stochastic element to how many behaviors a given household will implement, and this method quantifies and preserves the uncertainty in that stochasticity.

This process works for any set of predictor values. In a presumed-stationary world, we could generate new agents from the observed sets of predictor values or a multivariate distribution parameterized from the observed data. To test the effects of interventions, we could modulate the values of specific predictors, for example, increasing the values of effectiveness of defensible space behavior by some fixed or random value to understand how an education-outreach effort might work. The varying intercepts aspect of the model also opens the possibility of generating new towns in a princpled manner, as long as we are willing to posit that the new towns come from the same distribution as the observed towns. To do so, we draw values of α_{town}s from the posterior distribution of α.

Results

Summary Statistics

Figure 1 shows the distribution of number of defensible space behaviors, out of four possible, adopted per household by town. Across all towns, the modal number of behaviors adopted is four,the median is two, and the mean 2.37. Figure 1 also shows the number of survey responses in our dataset from each town, which are roughly proportional to the number of homes in the WUI in each town.

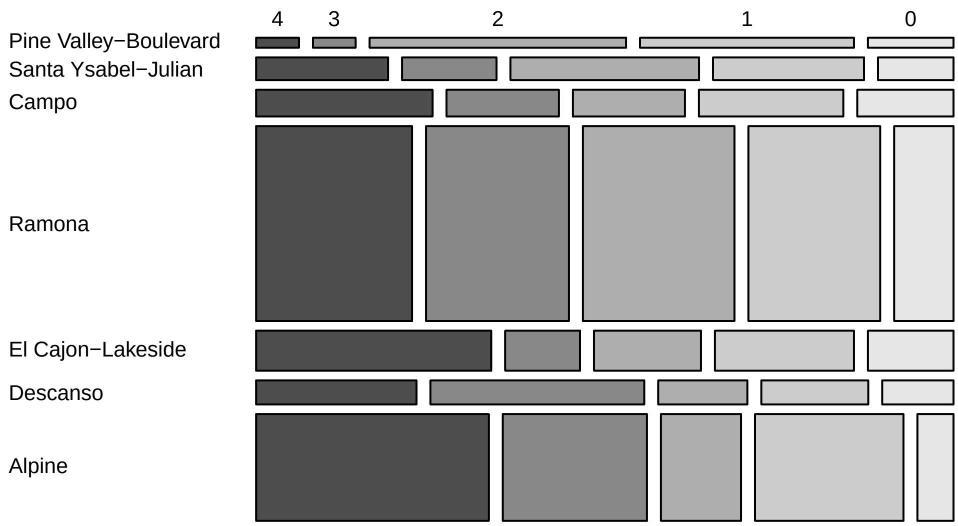

Figure 1: Number of defensible space behaviors adopted by town. Tile heights are proportional to the number of survey respondents per town, and widths are proportional to the number of people in that town having adopted that many behvaiors.

Model Coefficients

Table 1 presents parameter values and 95% credibility intervals for each of the predictors in the model. Belief in the effectiveness of defensible space behaviors is a strong positive predictor of implementation of defensible space behavior. Policy beliefs, which is an aggregate measure capturing ???, and perceived risk associated with wildfire are both negatively associated with defensible space adoption, but there is ambiguity around those relationships. Individuals who are closer to recent fires tend to have adopted more defensible space behavior, but this relationship also has significant uncertainty. There is substantial town-to-town variability in the base-rate of adoption: The distribution of town-level intercepts has its mean at 0.32 and a standard deviation of 0.23.

Table 1: Marginal parameter 95% credibility intervals for varying intercepts model of number of defensible space behaviors adopted by a household. α represents the (town-level) mean intercept (of $logit(p)$) and σ_{town} the standard deviation of the distribution of town-level α's.

	Mean	SD	Lower 95% CI	Upper 95% CI
β_P	-0.06	0.04	-0.14	0.03

	Mean	SD	Lower 95% CI	Upper 95% CI
β_E	0.52	0.05	0.43	0.61
β_R	-0.06	0.04	-0.15	0.02
β_D	-0.05	0.05	-0.15	0.04
α	0.32	0.12	0.07	0.55
σ_{town}	0.23	0.14	0.03	0.50
α_{Alpine}	0.55	0.09	0.38	0.72
α_{Campo}	0.22	0.15	-0.10	0.50
$\alpha_{Descanso}$	0.40	0.14	0.12	0.67
$\alpha_{ElCajon-Lakeside}$	0.35	0.12	0.12	0.58
$\alpha_{PineValley-Boulevard}$	0.11	0.23	-0.36	0.50
α_{Ramona}	0.37	0.06	0.25	0.49
$\alpha_{SantaYsabel-Julian}$	0.26	0.14	-0.03	0.53

Generating Agents

We now demonstrate how we can use the model to simulate agents. First, as a model check and demonstration of the process, we simulate new agents based on the responses of the 637 survey respondents. We then modulate the values of several predictors to show how we can use the process to simulate behavioral interventions.

For 30 survey respondents sampled at random, Figure 2 shows the distribution of model-predicted defensible space behaviors with their actual number of defensible space behaviors. Note that the model preserves substantial uncertainty around how many behaviors a household adopts, and that the level of uncertainty depends on the predictor values (for example a house in a town for which less data is available will have greater uncertainty).

We now simulate outcomes for two scenarios: One where perceived effectiveness of defensible space increases and one where perceived risk increases. In both cases the increase is a stochastic process, drawn from a normal distribution with mean two and standard deviation one (on the scaled-predictor scale). The modeled effect on defensible space behavior is presented in Figure 3.

References

McElreath, Richard. 2015. *Rethinking: Statistical Rethinking Book Package.*

R Core Team. 2016. *R: A Language and Environment for Statistical Computing.* Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Stan Development Team. 2015. *Stan: A C++ Library for Probability and Sampling, Version 2.10.0.* http://mc-stan.org/.

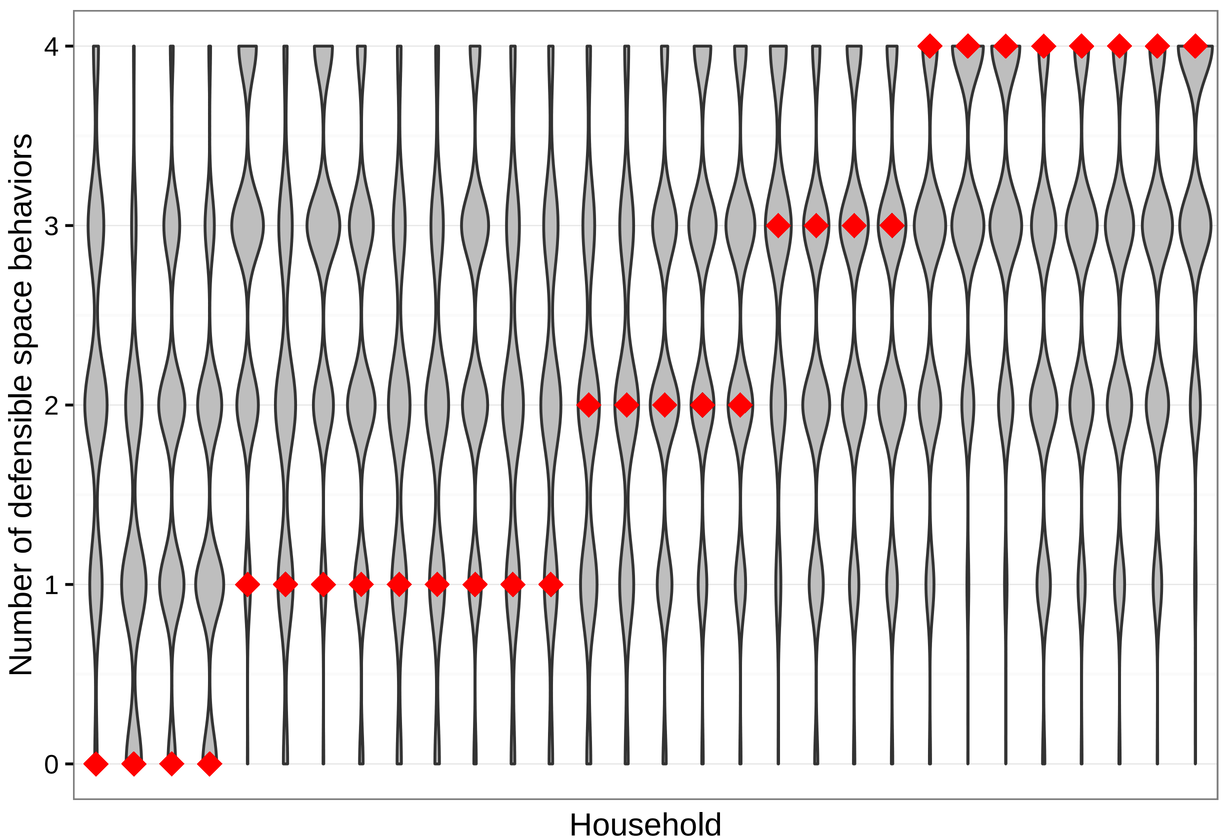

Figure 2: For 30 randomly sampled homes, red diamonds are empirical number of defensible space behaviors, and violin plots reflect the distribution of model-implied behaviors for simulated households with the same set of predictor values.

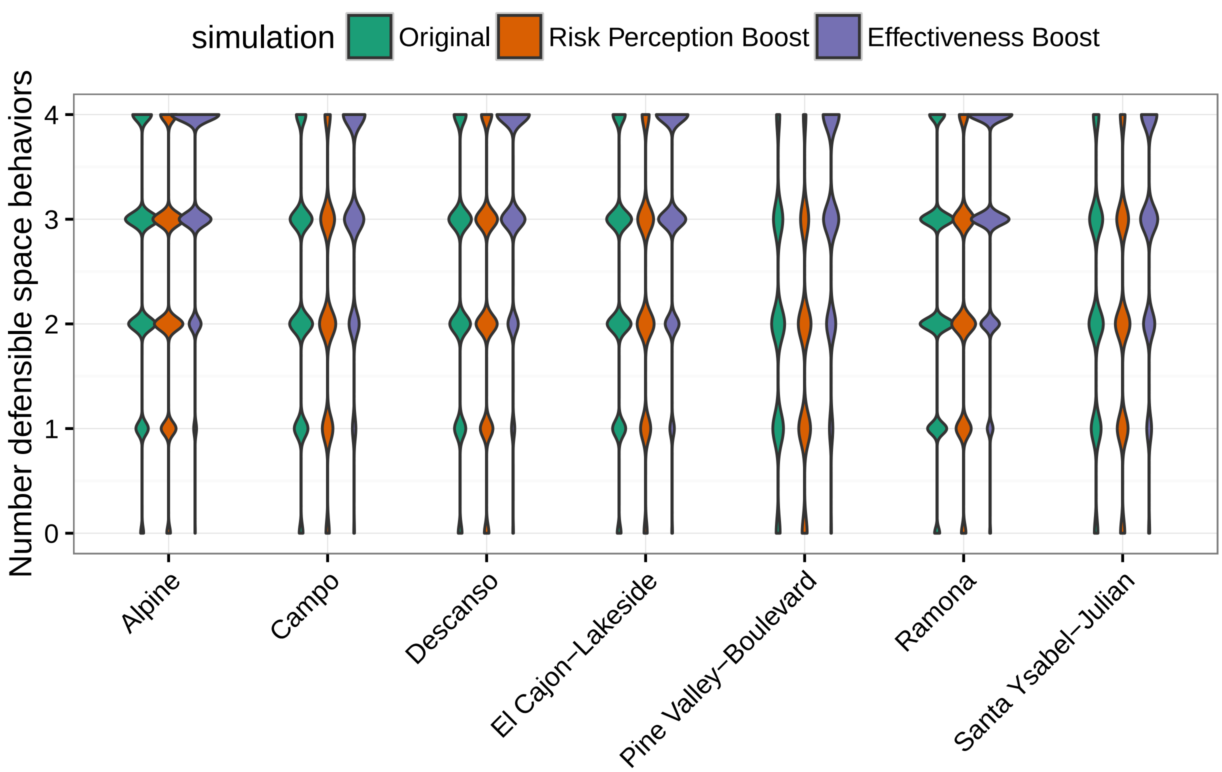

Figure 3: Effect of an increase in perceived risk of fire or perceived effectiveness of defensible space behavior on model-predicted number of defensible space behaviors.