Empirical generation of agent population for a coupled model of fire in the wildland-urban interface

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Introduction

Broad Justification: WUI fire is a problem and we need models that include society (Katie)

Already a problem, getting worse with climate change, DS behavior matters for the owner and broader fire patterns, therefore we need models that include homeowner behavior.

ABM Justification (Patrick)

Most models omit humans, econ models of behavior assume rational self-interest but that fails to capture key dynamics in collective action challenges like this. ABMs to the rescue: can capture social dynamics with agents responding to each other and can capture biophysical -> social feedback with agents responding to events in their environment.

Broad overview of our larger endeavor (Kenny?)

- Set out to build coupled model of fire and society.
- Located in San Diego because fire is big problem, potential for action, etc
- Full model situates homeowners on the landscape, simulates ignition and spread w/ homeowners responsive to social environment and fire experience, etc.
  - DS behavior empirically parameterized based on survey responses

Description of the system (Kenny)

Don't want to spend too much time here, but a paragraph on the SD WUI's salient features, especially the town structure, fire dynamics. Previous findings from this survey.

What is known about the drivers of DS behavior (Katie)

Particuarly, here we need to justify our use the effectiveness and risk constructs. Plus anything that can be said about social influences and proximity to fire is extra great.

Two-step process: generation & updating (Mike)

Two tasks for a working ABM: defining the population and their initial behavior (static) and updating their behavior (dynamic, function of physical and social environment).

We have cross-sectional survey data which provides an empirical foundation on which to build the population of agents. Data at a single timepoint cannot inform the dynamic updating process, so our updating is based on theory from the fire behavior literature. We defer a full descriptoin of agents' updating rules to the documentation of the coupled model but note that it employs a decision heuristic that incorporates social feedback in the form of the overall adoption rate in the agent's town and biophysicial feedback in the form of proximity to recent fire, as well as cognitive variables that prior research has demostrated are important predictors of the adoption of DS behavior. The cognitive and town-adoption variables used in the updating rules are the same as those used here in the generation of the population of agents.

Model for agent generation (Mike)

Here, we describe the motivation for, mechanics of, and findings from a survey-data-based empirical generation of a population of agents for a CHANS model. The parameterization is based on survey data and employs a Bayesian, multi-level model that quantifies and preserves uncertainty in human behavior and provides a natural, principled mechanism for generating agents.

Heterogeniety in behavior at town-level, don't want to ignore, but fixed effects over-learn. Pooling is awesome, quantifies uncertainty incorporating sample size, so we can do something principled in towns where we have few observations. Cite predictive benefits.

Generative aspect: Is there anything unique about Bayesian here? Don't have to make distributional assumption about posterior.

We identify households in the SDCNF by [**Patrick – finish this sentence; more detailed descrption below in methods**]. To generate an agent at each household location, we draw a set of predictor values from the ECDF (or maybe we have to make some distributional assumption to define a multivariate distribution to sample from), draw a set of parameters from the model's posterior distribution, and simulate a binomial trial to determine the number of DS behaviors that agent has adopted at the model initialization. We now describe this process in detail.

Methods

Data details (Kenny)

Survey collection, briefly, cite original paper.

WUI details (Patrick?)

We identified households in the WUI by . . .

- WUI deliniation
- Structure identification
- What counts as a household
- Assignment of households to towns
- Are all houses in our seven "towns"?

Model fitting (Mike)

- Note to self: Take out fire distance, maybe do formal model comparison and model averaging. Model comparison, m4 without distance; m5 without policy beliefs:

  WAIC pWAIC dWAIC weight SE dSE m5 3287.5 7.8 0.0 0.46 30.38 NA m4 3288.1 8.8 0.6 0.34 30.45 2.62 m3 3289.0 9.2 1.6 0.21 30.53 3.42

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 prior, $\mathcal{N}(0,1)$, for all four continuous predictors to reign-in overfitting. The model takes the form:

$$
\begin{aligned}
N_i &\sim binomial(4, p_i) \\
logit(p_i) &= \alpha_{town[i]} + \beta_P P + \beta_E E + \beta_R R + \beta_D ln(D) \\
\alpha_{town} &\sim Normal(\alpha, \sigma) \\
\alpha &\sim Normal(0.5, 1) \\
\sigma &\sim HalfCauchy(0, 2) \\
\beta_P &\sim Normal(0, 1) \\
\beta_E &\sim Normal(0, 1) \\
\beta_R &\sim Normal(0, 1) \\
\beta_D &\sim Normal(0, 1).
\end{aligned}
$$

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).

Populating the model (Mike)

- Defining joint distribution of predictors for each town

Rewrite this to match what we're doing now: for each house, draw one set of predictors and one set of parameters and generate a p. Bayesian models are generative, and we now describe how we 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.

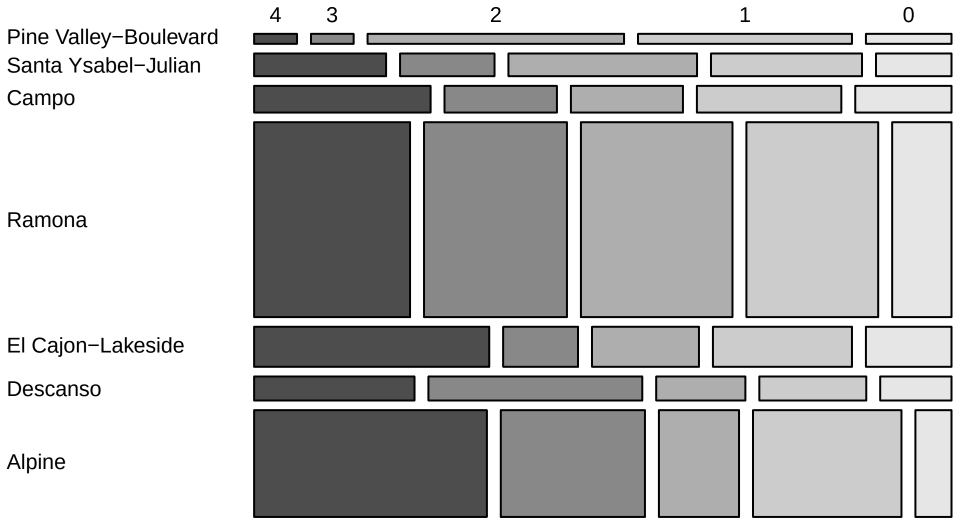

Figure 1: Number of defensible space behaviors adopted by town. Tile heights are proportional to the number of survey respondents per town, and widths are proportional to the number of people in that town having adopted that many behvaiors.

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 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
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	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.

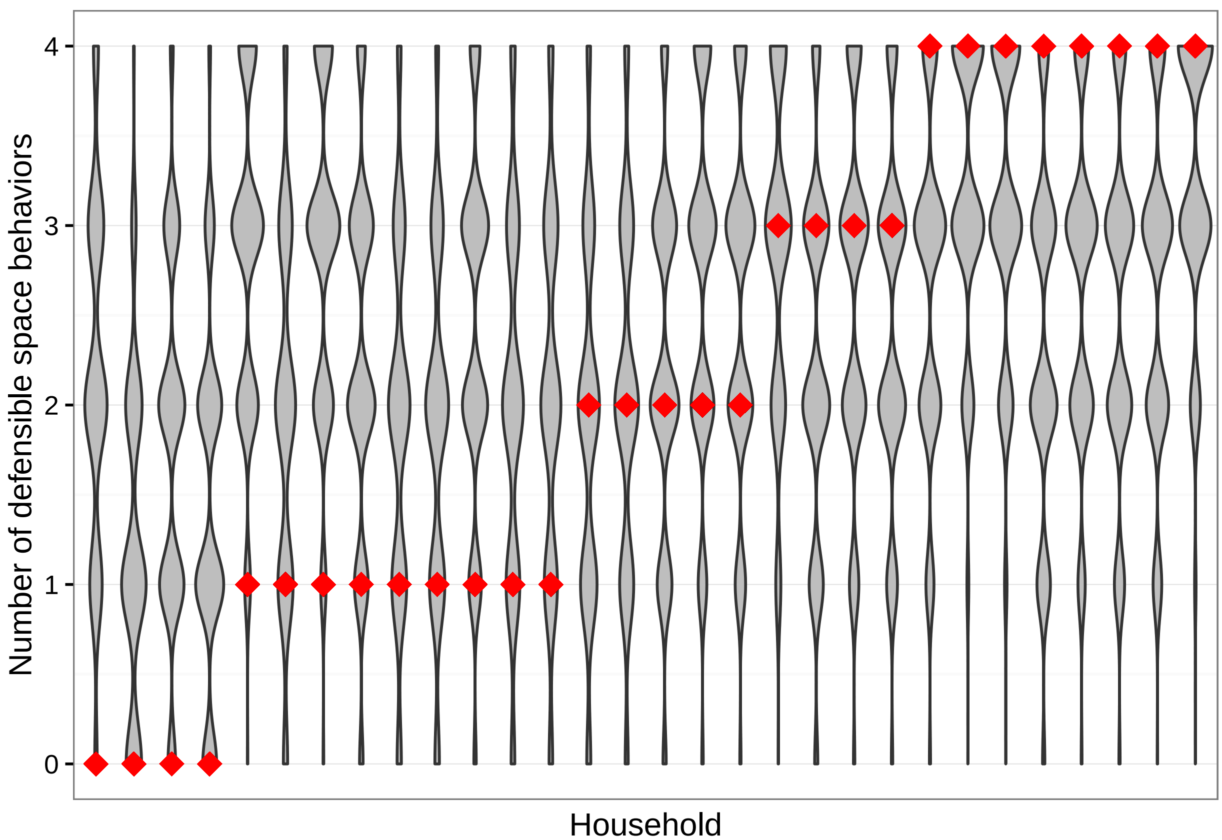

Figure 2: For 30 survey respondents sampled randomly, red diamonds are empirical number of defensible space behaviors, and violin plots reflect the distribution of model-implied behaviors for simulated households with the same set of predictor values.

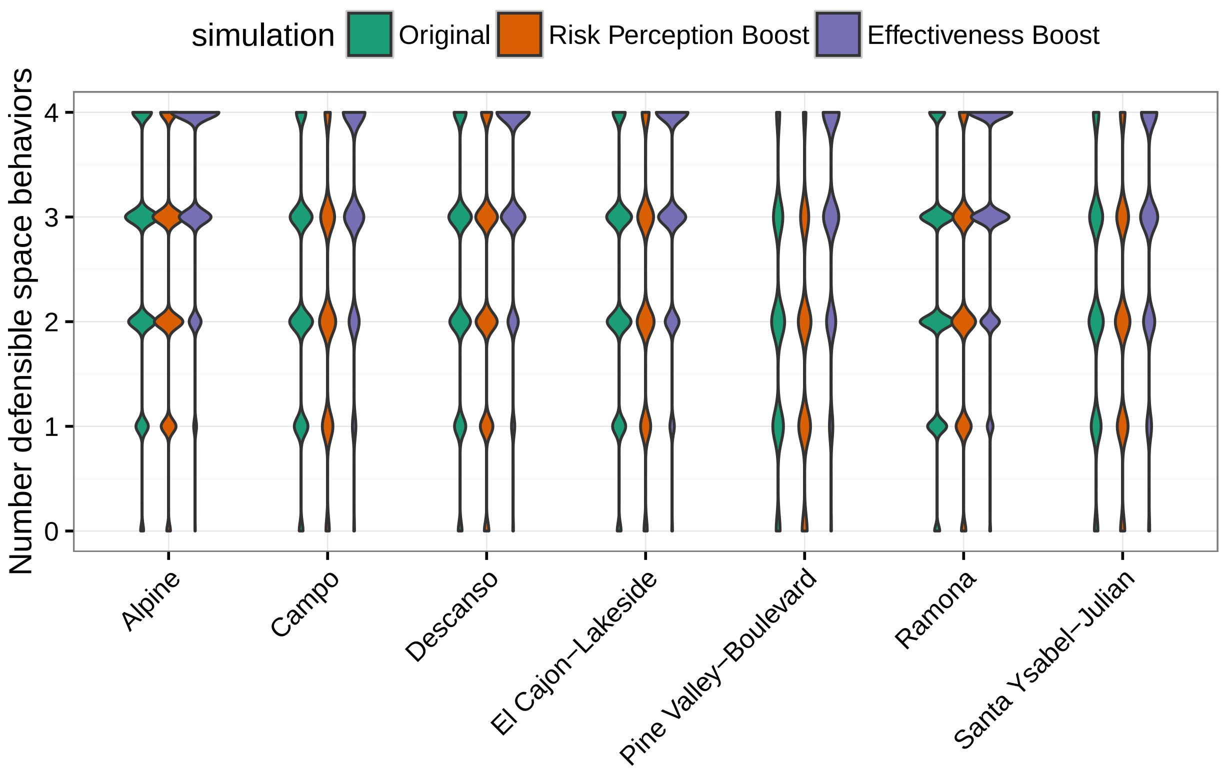

Figure 3: Effect of an increase in perceived risk of fire or perceived effectiveness of defensible space behavior on model-predicted number of defensible space behaviors. Green violins show the distribution of model-implied number of DS behaviors by town. Red and purple violins, respectively, show model implied number of DS behaviors with every individual in the population having had an increase in their perception of risk or effectiveness.

Discussion

Substance of what we found (Katie and/or Kenny)

How does it fit with other DS behavior research? With other findings from this survey?

How the ABM stuff works and will fit into ABM and coupled model (Mike)

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/.