A Tool for Sharing Empirical Models of Climate Impacts

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Motivation

Scientists, policy advisors, and the public struggle to synthesize the quickly evolving empirical work on climate change impacts. The Integrated Assessment Models (IAMs) used to estimate the impacts of climate change and the effects of adaptation and mitigation policies are often out-of-date with respect to empirical results.

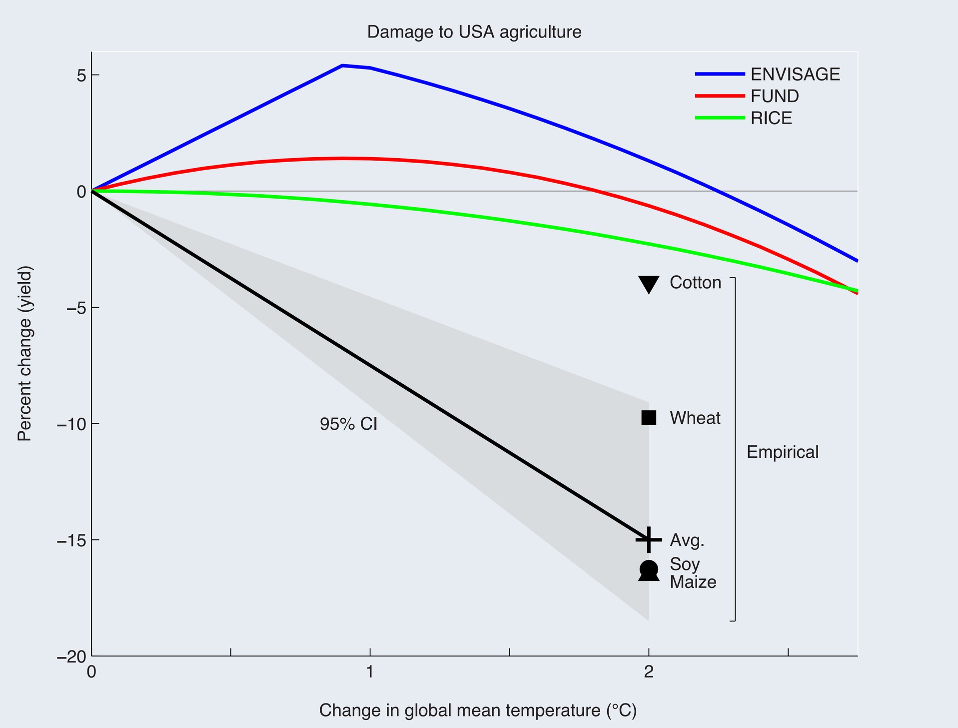


Figure: Reproduced from [1]. Black: Projected changes in yields using estimated models and the projected exposure of USA croplands. Changes averaged by cropland planted in a given crop. Comparable damage functions from ENVISAGE, FUND and RICE are colored.

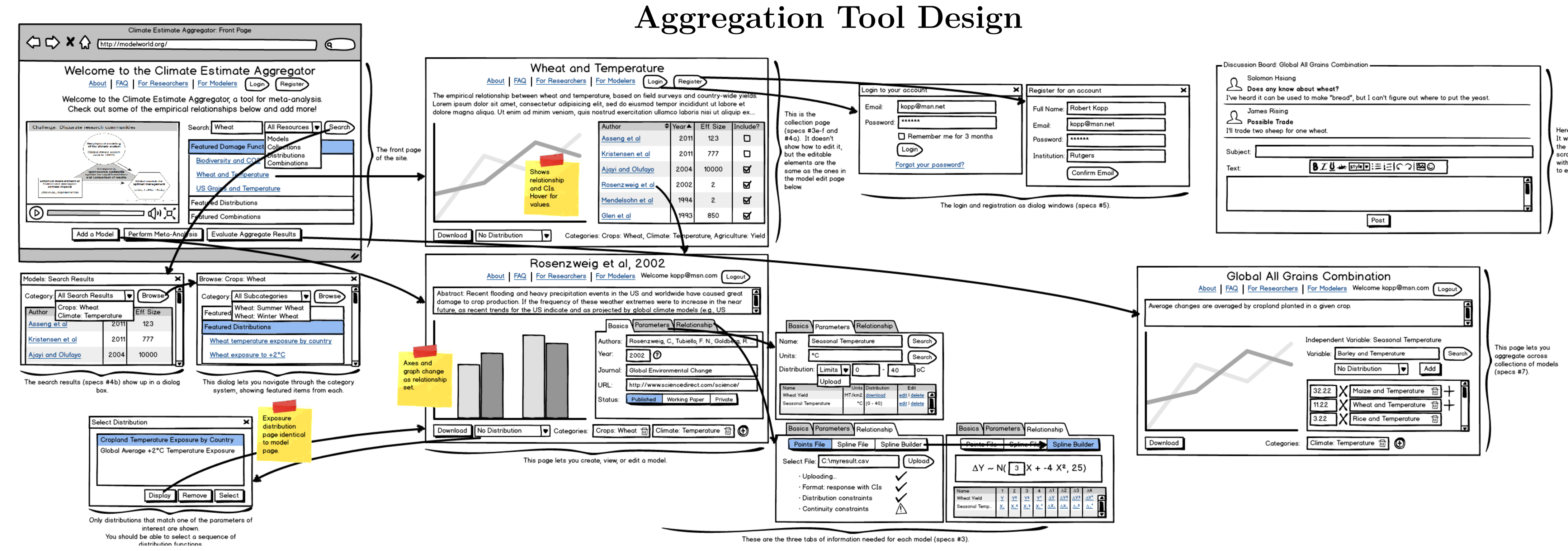
A New Tool

We create an online tool for exploring, analyzing, combining, and communicating a wide range of impact results, and supporting their integration into IAMs. The tool uses a new database of statistical results, which researchers can expand both in depth (by providing additional results that describing existing relationships) and breadth (by adding new relationships). It can automatically generate new meta-analyses as new parameter estimates are added, and provide these to IAMs to be incorporated into comprehensive impact estimates.

Applications

Scientists can use the tool to quickly perform meta-analyses of related results, using Bayesian techniques to produce pooled and partially-pooled posterior distributions. Policy advisors can apply the statistical results to particular contexts, and combine different kinds of results in a cost-benefit framework. The general public can better understand the many estimates of climate impacts and their range of uncertainty by exploring these results dynamically, with maps, bar charts, and dose-response-style plots.

Aggregation Tool Design



Model Types

Parameter estimates, represented as probability distributions, are the building-blocks of the database.

1. Single parameter distributions

An unconditional probability density function, which may take any form, input either as a spline or a sampled function.

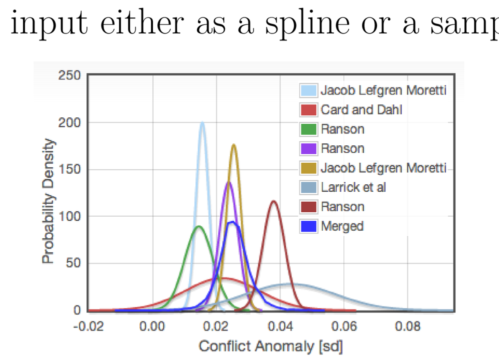


Figure: Climate and Conflict [2]. PDFs represent parameter estimates for the US and the Bayesian aggregated result, of the effect of a standard deviation change in climate on violence, in terms of a z-score.

2. Dose-Response parameter

A non-linear response, with a conditional PDF over the parameter values for every value of the "dose" variable.

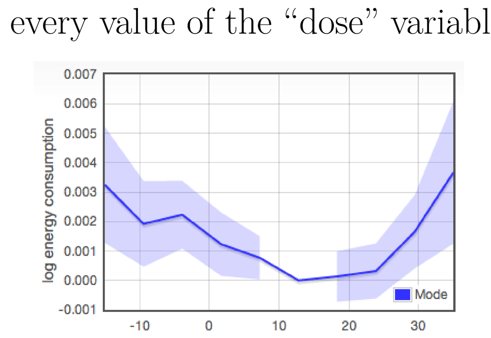


Figure: Energy and Temperature [3]. The relationship between log energy consumption and daily temperature from US data. 95% confidence intervals are shown.

3. Categorical independent variable

When the independent variable takes discrete or categorical, the model is represented as a bar graph.

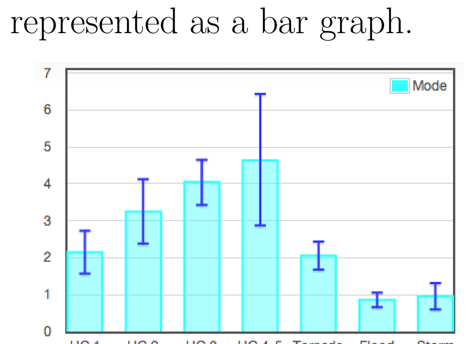


Figure: Damages and Storms [4]. Impact from various categories of hurricanes, and from tornadoes, floods, and severe storms. Error bars show 95% confidence intervals.

4. Categorical dependent variable

When the probability distribution is defined over a discrete dimension, the model is represented as a probability mass function.

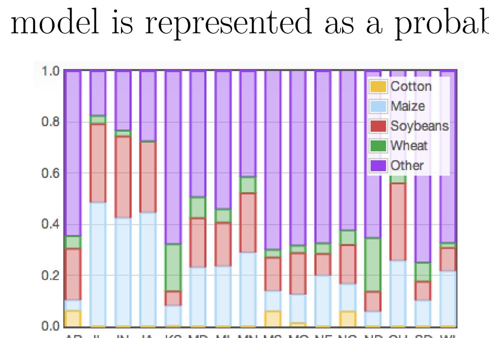


Figure: Crop Areas [5]. Portion of farm area by state, for cotton, maize, soybeans, and wheat. Only states with at least 25% of crop area allocated to those four crops are shown.

Merging

Three methods are used to determine a meta-analysis merging of parameter values.

Pooled Estimates

A pooled estimate assumes that all parameter estimates describe the same underlying variable, and that they are independent.

$$p(\theta) = p(\cap_{i=1}^{N} \theta = \theta_i) \propto \prod_{i=1}^{N} p(\theta_i)$$

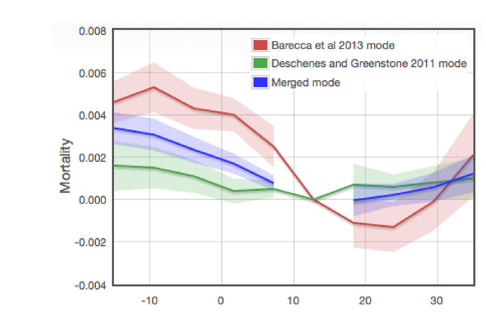


Figure: Pooled estimate of log mortality as a function of temperature [3, 6]. The 95% confidence interval of the pooled result does not overlap with the individual estimates when they are far from each other.

Hierarchical Bayesian Modeling

We apply Hierarchical Bayesian modeling, which allows for "partial-pooling", whereby the degree to which estimates inform the same underlying parameter is simultaneously estimated.

$$\theta_i \sim N(\mu, \tau^2)$$
$$y_i \sim N(\theta_i, \sigma_i^2)$$

where μ is the underlying parameter, τ^2 is the variance between models of their individual parameters. We apply non-informative distributions to μ and τ. θ_i is the parameter for model i, y_i is the estimated value of that parameter, and σ_i^2 is the standard error of that estimate. Variables in green are given; variables in red are simultaneously estimated.

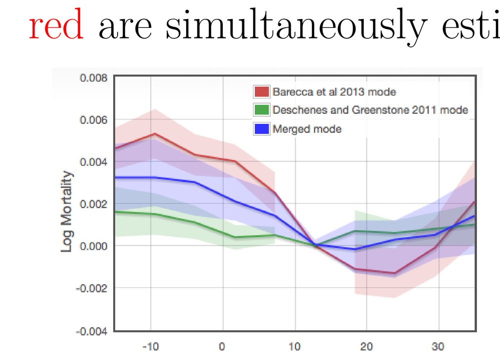
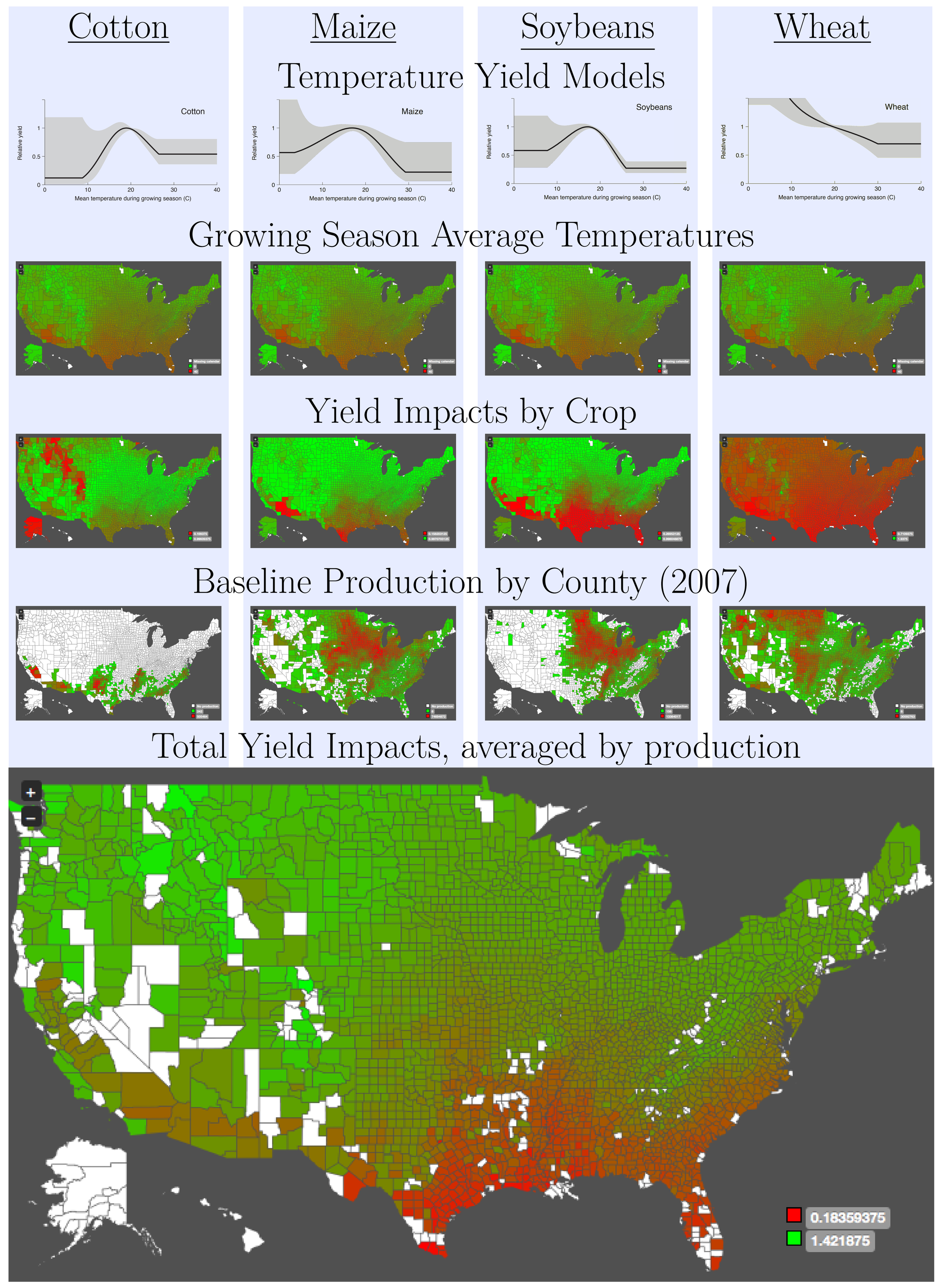


Figure: Bayesian estimate of log mortality as a function of temperature [3, 6]. The confidence intervals on μ are wide, reflecting the uncertainty in resolving the two estimates.

Additionally, the spread between models can be better preserved, by sampling from τ.

Example: Average Crop Impacts

Below, we apply models for the impact of growing season temperature on yields for four different crops. We calculate growing season temperatures using state-specific planting and harvesting days [7]. Then, we generate an average yield impact, by weighting the effects by baseline crop productions by county [5].



Acknowledgments

This material is based upon work supported by the National Science Foundation under Grant No. 1000152207.

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[2] Hsiang, S. M., Burke, M., & Miguel, E. (2013). Quantifying the influence of climate on human conflict. Science, 341(6151), 1235367.

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[4] Deryugina, T. (2011). The dynamic effects of hurricanes in the US: the role of non-disaster transfer payments.

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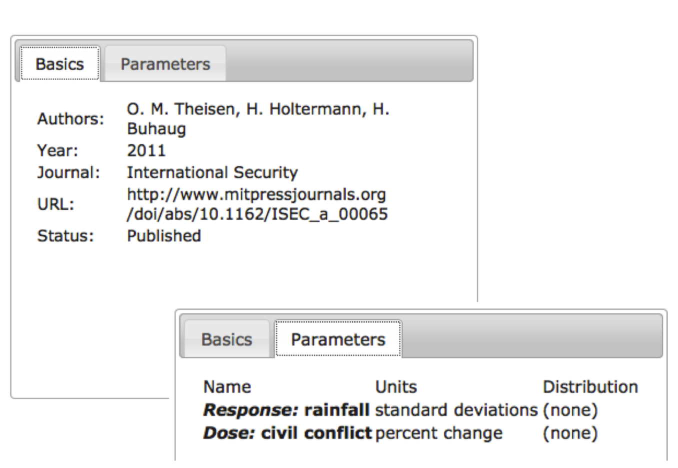
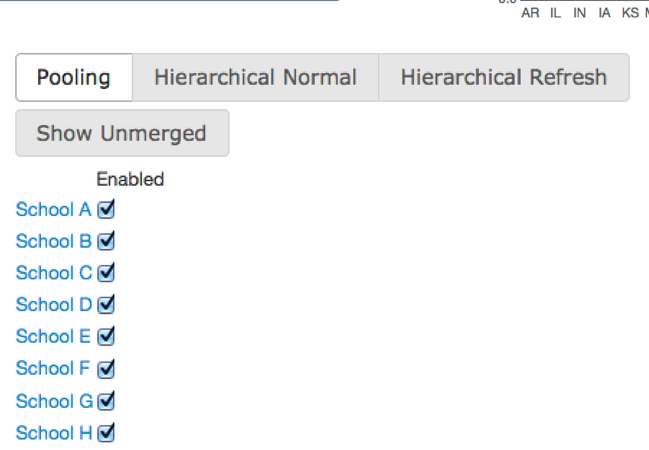
[7] Sacks, W.J., D. Deryng, J.A. Foley, and N. Ramankutty (2010). Crop planting dates: an analysis of global patterns. Global Ecology and Biogeography 19, 607-620. DOI: 10.1111/j.1466-8238.2010.00551.x.

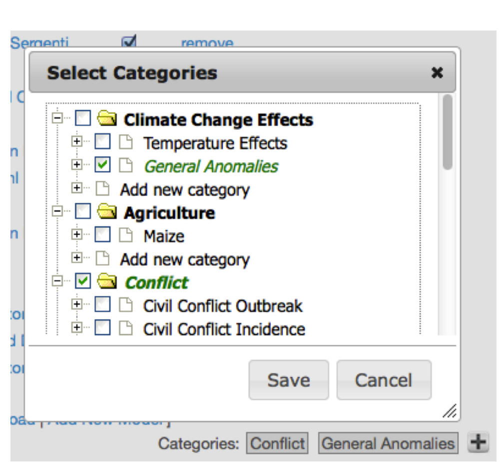


Paper/model attributes

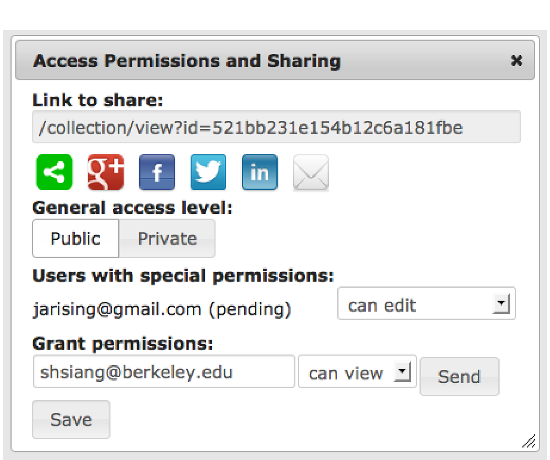


Immediate meta-analyses

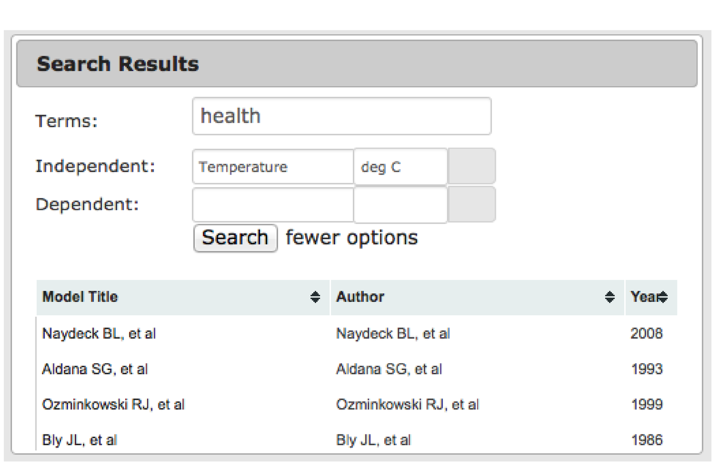
Filter by characteristics



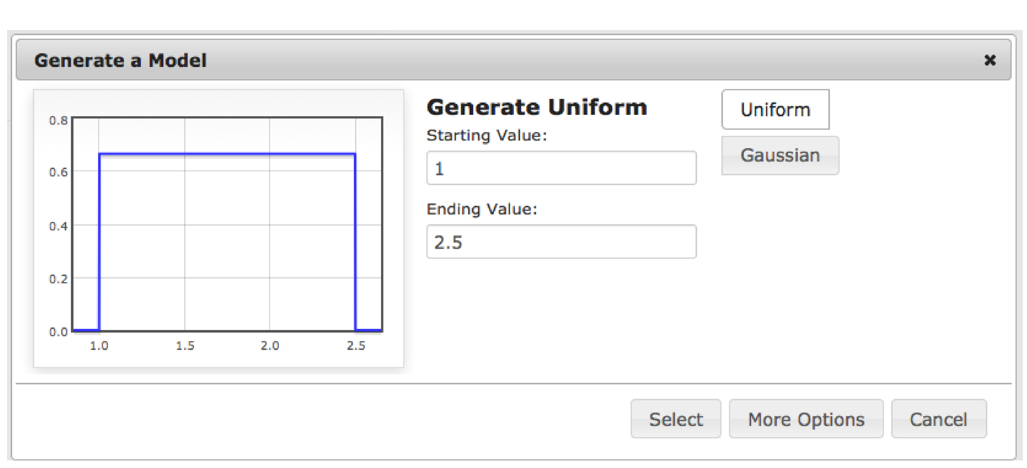
Multiple categorization



Access/moderation system



Parameter-aware search



Simple ways to generate new models.