



# Evaluation of policy options using uncertainty analysis of complex-system model results

Patrick Finley  
[pdfinle@sandia.gov](mailto:pdfinle@sandia.gov)

3/2/2011



# Overview

- **Intro to uncertainty analysis**

- Get more information out of model runs
- Provide estimate of quality and reliability of results
- Determine when the model sufficiently detailed

- **Robust policy options overview**

- What makes a policy robust?
- Why are robust policies superior?

- **Example of robust policy design:**

- Sandia/VA pandemic influenza study
- Lessons learned
- Methods for uncertainty-driven policy design



# Terms

- Uncertainty analysis: Determining sources and effects of uncertainties in model design and inputs
- Categories of uncertainty
  - Aleatory: Related to chance
  - Epistemic: Related to (lack of) knowledge
- Aleatory: aka Stochastic
- Epistemic: aka Parametric
- Structural uncertainty (Type III)
- Design of Experiment (DOE): Planning model runs and parameter variations to answer question adequately and efficiently



# Basics of uncertainty analysis

- Create design of experiment to answer your question efficiently
- Perform Sensitivity Analysis (SA) to determine which inputs have the most effect on outputs
- Run uncertainty quantification (UQ) to identify sources of model uncertainty and how best to reduce it
- Run statistical significance tests to gauge reliability and quality of study results
- Repeat until satisfactory level of confidence reached.



## Parameter sweeps

- Run model many times
- Vary single model input while holding all others fixed
- Plot output vs. each input

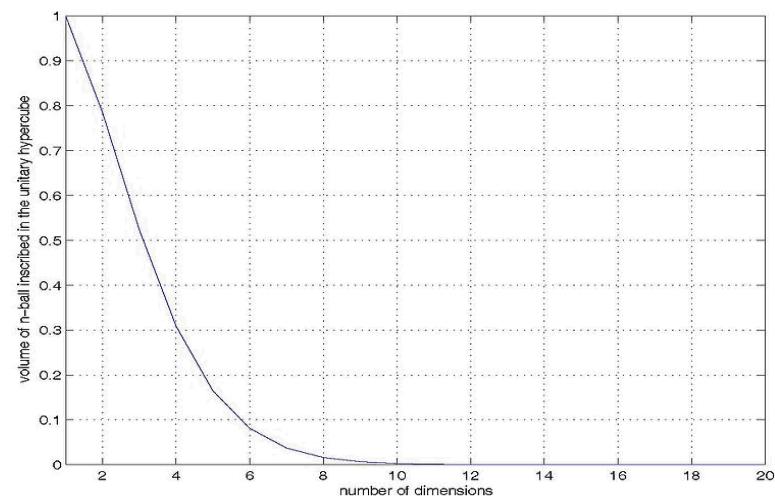
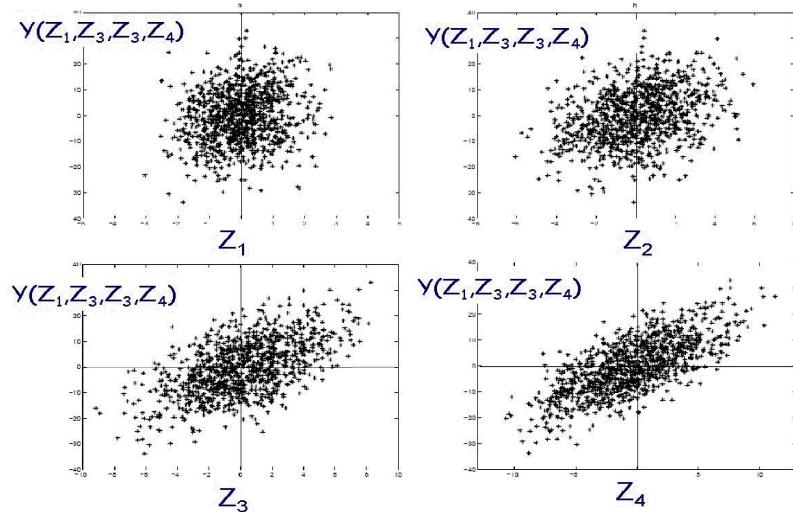
## Pros:

- Fast to set up
- Easy to interpret

## Cons:

- Takes a lot of runs
- Ignores interactions
- Only looks at small portion of parameter space.

# Simple sensitivity analysis



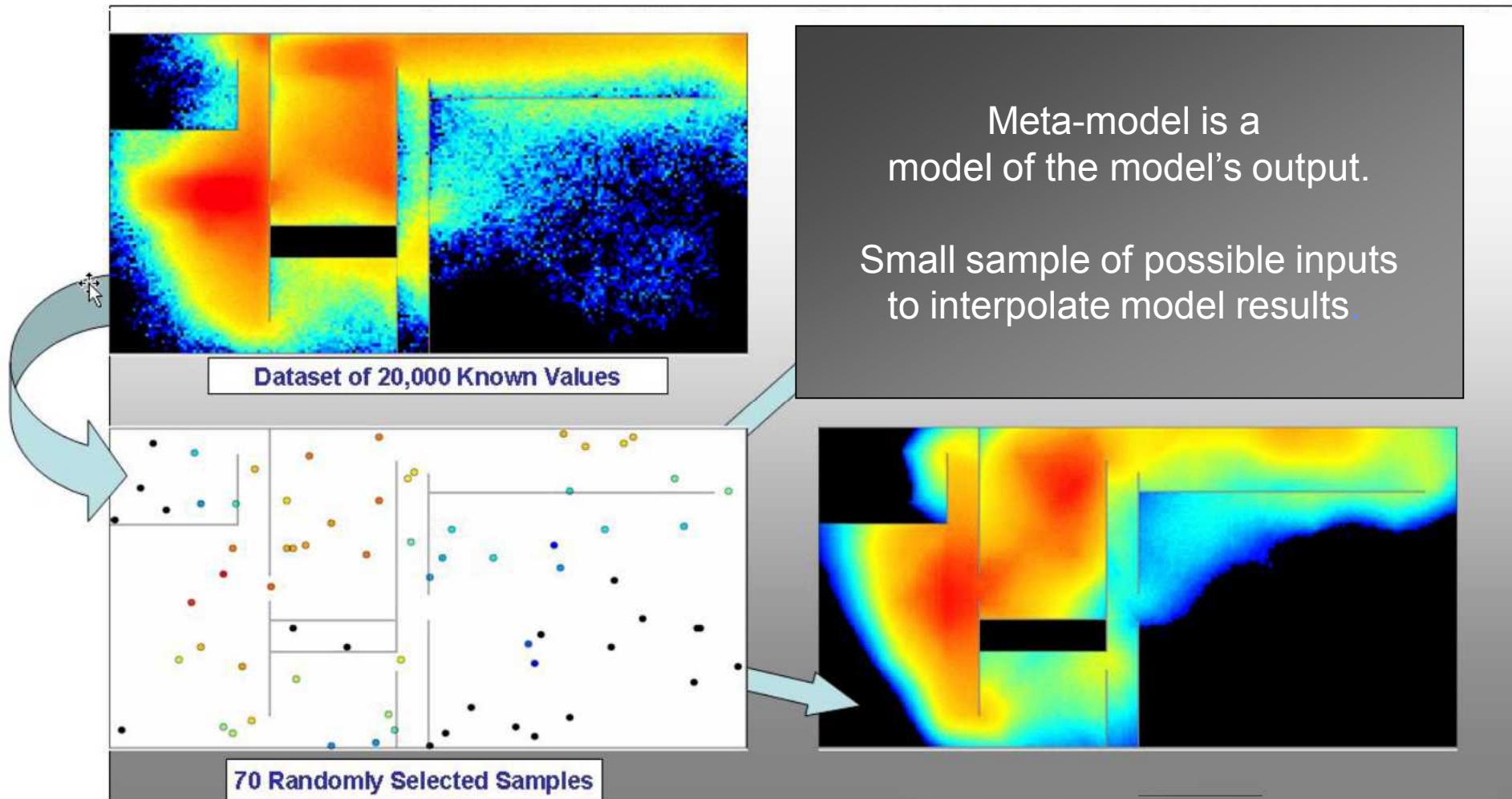


# Better Sensitivity Analysis Methods

- Multivariate Global Sensitivity Analysis
  - Run model many times
  - Vary all of the input parameters at once
  - Analyze relationship of inputs to outputs
- Pros:
  - Looks at all possible values of all parameters.
  - Lets you see interaction effects
- Cons
  - Can't directly interpret results
  - Standard methods require HUGE numbers of runs



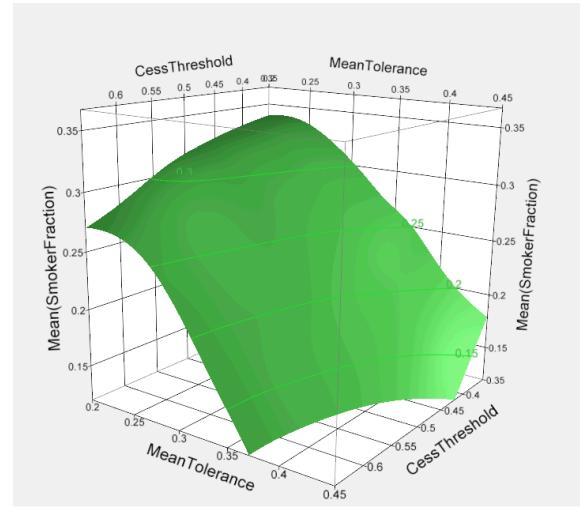
# Meta-models for Sensitivity Analysis





# Why use meta-models?

- Far fewer model runs needed (~1%)
- More flexible and stable estimates
- Determine interaction effects
- Fast, approximate model results for input combinations that weren't run
- Best bets: Gaussian process, radial basis functions , adaptive splines, and polynomial chaos expansion



## Model Report

Column	Total			sensitivity			hMid			pFill			lFull			consumptionTime		productionTime	
	Theta	Sensitivity	Main Effect	Interaction	Interaction	Interaction													
sensitivity	0.0071275	0.0013994	0.0007988				2.7455e-5	0.0004133	0.0001599				1.3507e-8		1.1883e-9				
hMid	1.0880024	0.2295383	0.1078837	2.7455e-5				0.1215762	3.3322e-5				0.0000177		7.1324e-9				
pFill	1.1111107	0.8873233	0.7630665	0.0004133	0.1215762				0.0022544				1.1846e-5		9.9351e-7				
lFull	0.1427269	0.0059568	0.0035089	0.0001599	3.3322e-5	0.0022544							2.3506e-7		5.8587e-9		0		
consumptionTime	0.0010747	0.0000354	0.0000056	1.3507e-8	0.0000177	1.1846e-5	2.3506e-7												
productionTime	8.7114e-5	1.0103e-6	2.6351e-9	1.1883e-9	7.1324e-9	9.9351e-7	5.8587e-9							0					

$$\mu \quad \sigma^2$$

$$63.366829 \quad 527.00581$$

$$-2\text{LogLikelihood}$$

$$864.15235$$

Fit using the Cubic correlation function.





# What does uncertainty analysis provide?

- Determines which parameters are most effective in changing model results
- Shows where improved data are needed
  - Better estimates of insensitive parameters not important
  - Important but poorly known parameters can use better data.
- Shows what you can safely ignore in your model
- Gives hard estimates on quality of model results under different scenarios.
- Answers questions of how trustworthy model results really are.



# Robust policy options

- Single policies or combinations which create the desired outcome under a wide range of possible scenarios
- Options or interventions often designed for specific scenario conditions
- Policies are implemented in a wide range of scenarios
- Some policies may not perform well under unexpected conditions.
- Modeling policy outcomes over all conceivable implementation scenarios helps to find robust options.



## Example of Robust Policy Design

- *Effective, Robust Design of Community Mitigation for Pandemic Influenza: A Systematic Examination of Proposed US Guidance* (Davey, Glass, Min, Beyeler, Glass, 2008)
- Evaluated seven interventions (e.g. school closing, quarantine, etc.) on severity of influenza outbreak for variety of assumptions.
- About 2 million model runs to explore combinations of parameters
- Ranked treatment and mitigation strategies



# Pandemic study generated lots and lots of data

TABLE 1: 90% compliance

Combinations with infected attack rate 10% or less are green, 25% to 10% are pink

ID Factor		None	ASsd	CTsd	CTsd,ASsd	S	S,ASsd	S,CTsd,ASsd	S,CTsd
0.75	None	2780	1872	1111	624	221	207	124	119
	T	1560	765	373	237	164	150	122	117
	Q	984	562	267	237	178	151	125	141
	P	711	379	217	184	161	138	114	123
	Q,T	600	324	218	159	140	132	119	120
	Q,P	329	298	166	160	148	129	121	130
	Pex	251	209	149	150	146	134	106	111
	Q,Pex	267	187	138	145	122	117	104	108
	None	4965	3843	3941	3013	2274	1298	199	170
	T	4111	3064	2741	1815	665	369	157	129
1.00	Q	3599	2665	2007	1321	718	420	174	145
	P	3192	2190	1214	735	278	250	143	129
	Q,T	2823	1880	924	638	334	213	135	133
	Q,P	2545	1531	617	415	249	196	144	128
	Pex	1776	1035	598	371	218	194	140	130
	Q,Pex	1287	814	323	257	207	178	128	144
	None	6246	4916	5436	4375	4723	3588	506	278
	T	5554	4228	4581	3540	3268	2090	233	173
	Q	4999	4064	3963	3239	2810	1964	314	230
	P	3487	3480	3344	2551	1455	791	180	162
1.25	Q,T	4334	3353	2925	2174	1350	767	200	172
	Q,P	3952	3007	2432	1513	670	504	173	172
	Pex	3117	2291	2007	1333	675	350	168	137
	Q,Pex	2686	1889	1138	541	422	285	163	153
	None	7134	5625	6462	5264	6104	5007	1689	534
	T	6541	5038	5743	4527	5120	3882	484	239
	Q	5986	4979	5168	4353	4568	3709	867	438
	P	5573	4293	4632	3592	3627	2278	293	197
	Q,T	5288	4268	4328	3460	3362	2297	338	239
	Q,P	4902	3854	3778	2900	2706	1465	270	220
1.50	Pex	3967	3053	3124	2370	2046	1117	246	179
	Q,Pex	3485	2660	2376	1618	1285	702	247	199
	None	8230	6525	7729	6334	7790	6675	5256	2241
	T	7794	6001	7192	5721	7139	5903	3100	641
	Q	7285	6084	6701	5732	6636	5736	3873	2108
	P	6923	5307	6227	4938	5964	4704	1246	389
	Q,T	6687	5445	6002	4987	5744	4720	1771	639
	Q,P	6182	4940	5478	4394	5141	3943	855	400
	Pex	5233	4020	4611	3559	4144	3156	659	336
	Q,Pex	4710	3652	3984	3030	3492	2459	559	335
2.00	None	8850	7107	8473	6996	8610	7631	7035	4310
	T	8540	6819	8075	6449	8159	7034	5676	2004
	Q	8087	6791	7649	6570	7721	6885	5996	4135
	P	7777	5997	7248	5761	7268	6038	3788	860
	Q,T	7584	6187	7042	5867	7077	6051	4429	1765
	Q,P	7112	5662	6519	5308	6534	5417	3014	813
	Pex	6131	4698	5617	4378	5413	4306	2043	602
	Q,Pex	5604	4389	5031	3897	4764	3780	1469	581
	None	9237	7545	8929	7465	9091	8213	8062	5656
	T	9003	7054	8623	6956	8776	7722	7157	3758
2.50	Q	8626	7261	8259	7139	8410	7606	7216	5447
	P	8384	6472	7933	6302	8052	6902	5687	1897
	Q,T	8188	6697	7768	6515	7861	6921	6004	3465
	Q,P	7753	6194	7284	5909	7396	6340	4983	1786
	Pex	6803	5216	6353	4964	6327	5155	3803	1135
	Q,Pex	6276	4906	5832	4561	5758	4663	3124	971

Each cell represents mean of 100 model runs

Colors indicate quality of solution

Key:

T = Treatment

S = School Closure

Q = Quarantine

ASsd = Adult distancing

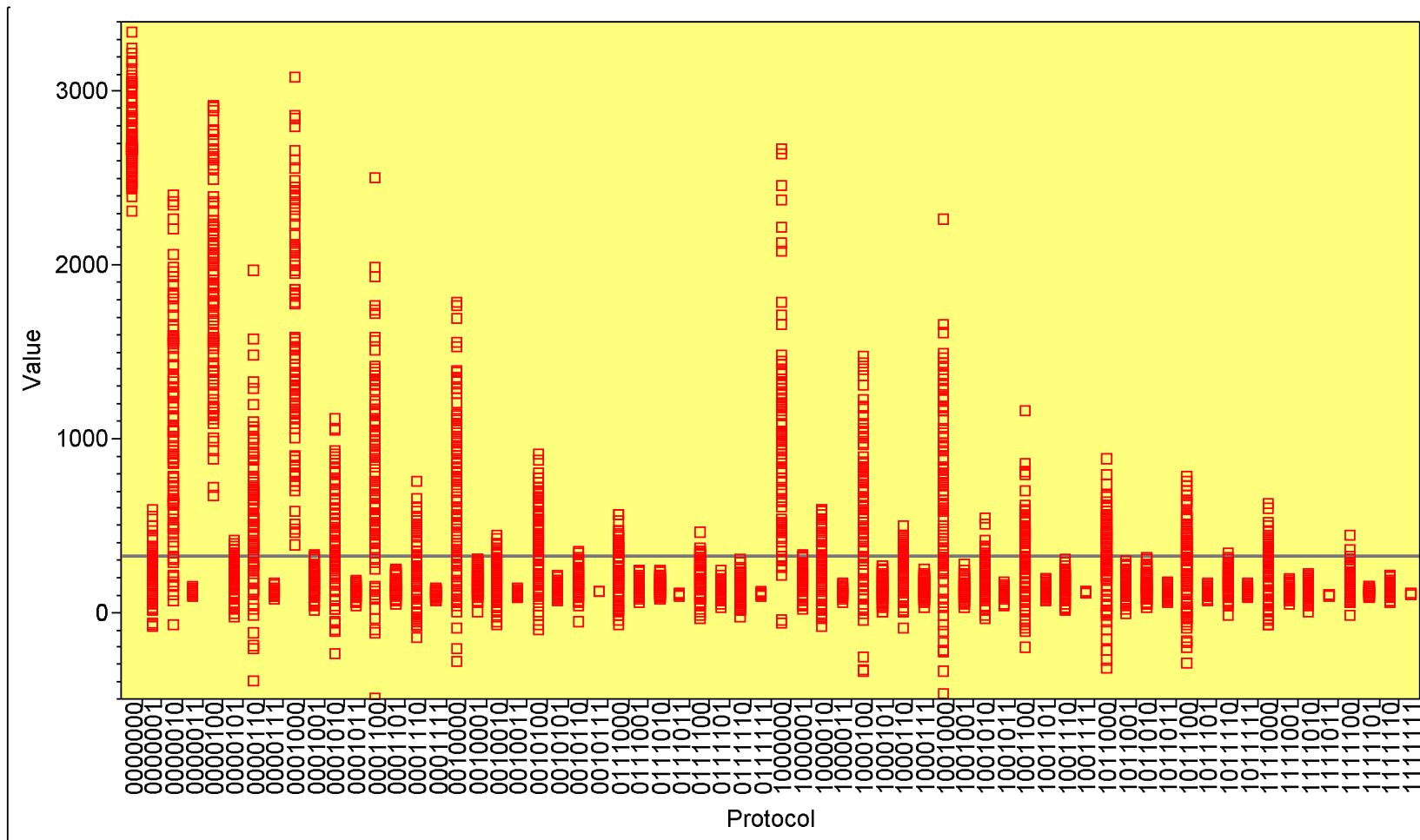
P = Prophylaxis

CTsd = Child distancing

Pex = Extended Prophylaxis



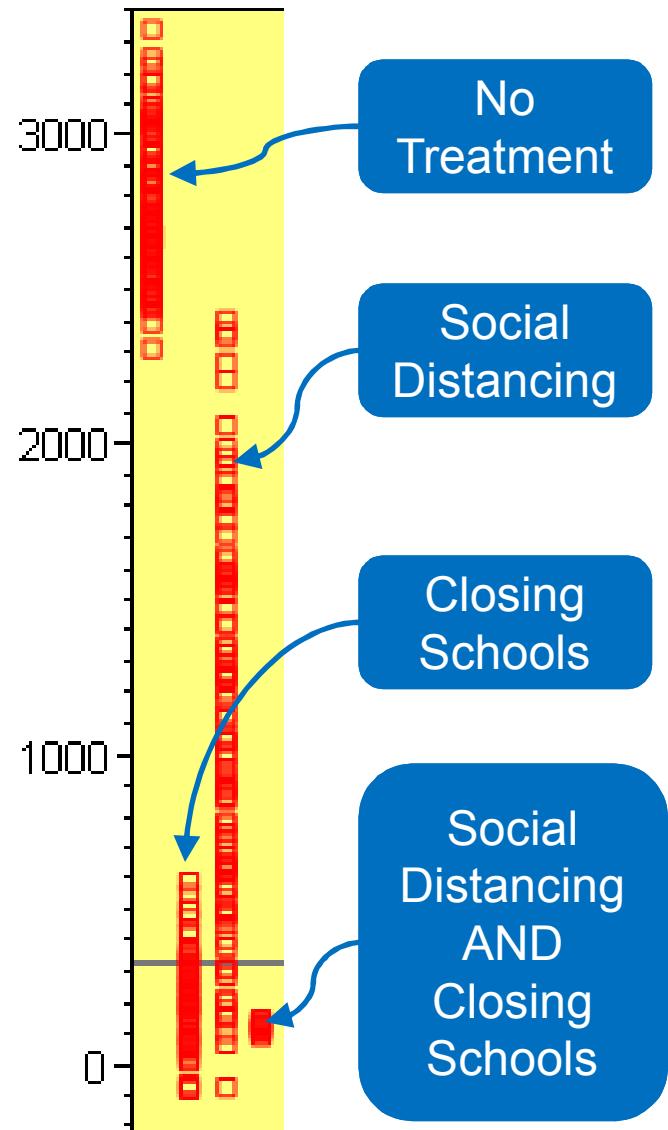
# Scatter plot of pandemic study results shows numbers of people infected and variability in model





## Desirable outcomes and low variability characterize Robust Policies.

- ❑ Each policy tried on 100 random social networks
- ❑ 2,780 cases expected with no treatment
- ❑ Closing schools is best single option
  - ❑ Mean = 137 cases
  - ❑ Moderate variation
- ❑ Social distancing is not as effective
  - ❑ Mean = 987 cases
  - ❑ Wide variation
- ❑ Both policies in conjunction create robust solution
  - ❑ Mean = 118 cases
  - ❑ Narrow variation
- ❑ Robust solution:
  - ❑ Good outcome
  - ❑ Most stable to uncertainty





## Uncertainty analysis best practices for complex adaptive system model evaluation

- Define policy inputs as numerical ranges rather than categorical choices whenever possible
- Run simple parameter scans to get a feel for effects
- Run near-orthogonal Latin hypercube space-filling design on small sets of runs ( $n = \sim 200$ )
- Document sensitivity and interactions with meta-models
- Look for interesting peaks and troughs in state space and distributions
- Trace uncertainty from sources to results
- Apply uncertainty to rank policy options
- Use uncertainty to guide further refinement