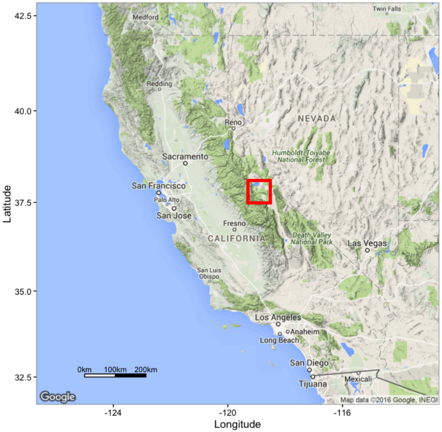
A probabilistic hazard mapping tool for the Long Valley volcanic region

Regis Rutarindwa, Elaine Spiller, Marcus Bursik, Andrea Bevilacqua

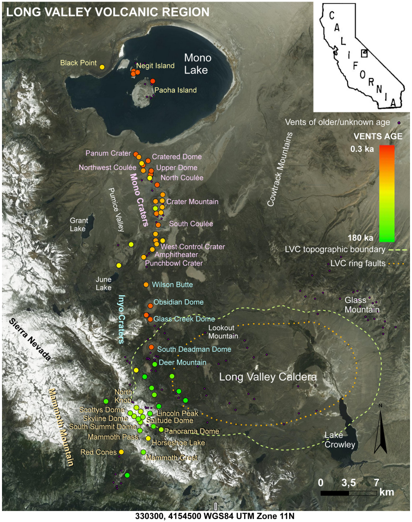
August 14, 2017

Long Valley



42.5
40.0
37.5
35.0
32.5
Latitude
-124
-120
-116
Longitude
Medford
Twin Falls
Redding
Reno
NEVADA
Sacramento
Humboldt-Toiyabe National Forest
San Francisco
Palo Alto
San Jose
Fresno
CALIFORNIA
Death Valley National Park
Las Vegas
San Luis Obispo
Los Angeles
Anaheim
Long Beach
San Diego
Tijuana
Mexicali
0km 100km 200km
Google
Map data ©2016 Google, INEGI

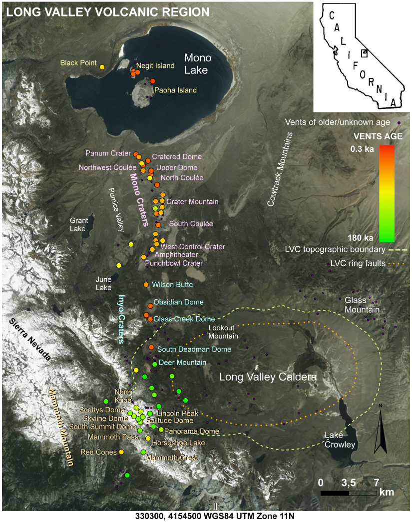
Long Valley Volcanic Region



Long Valley caldera

- Formed $760,000$ years ago
- Potentially active
  - ★ thermally activity
  - ★ ground deformation
- Threat Potential: High

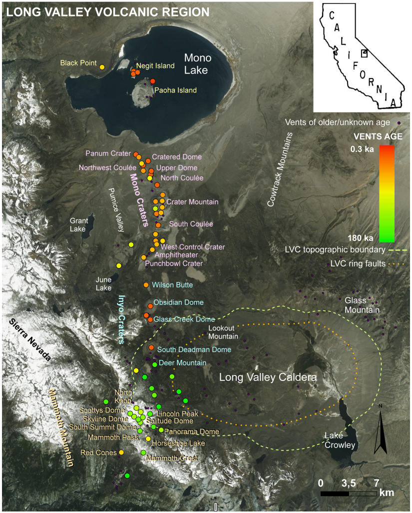
Long Valley Volcanic Region



Mono-Inyo craters

- 17 km long
- ≈ 30 craters
- Last eruption: 215 years ago
- Threat Potential: High

Long Valley Volcanic Region



330300, 4154500 WGS84 UTM Zone 11N

Mono-Inyo craters

- 17 km long
- $\approx$ 30 craters
- Last eruption: 215 years ago
- Threat Potential: High

Potential loss:

- Town of Mammoth Lakes 8000 - 30,000 inhabitants
- Highway and roads
- Los Angeles city aqueduct

Goals

- Integrate various sources of knowledge to
  - compute hazard probabilities for the Long Valley volcanic region
  - quantify various epistemic and aleatoric sources of uncertainty

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  - compute hazard probabilities for the Long Valley volcanic region
  - quantify various epistemic and aleatoric sources of uncertainty
- develop a fast and flexible tool for understanding the impact of hazards probabilistically

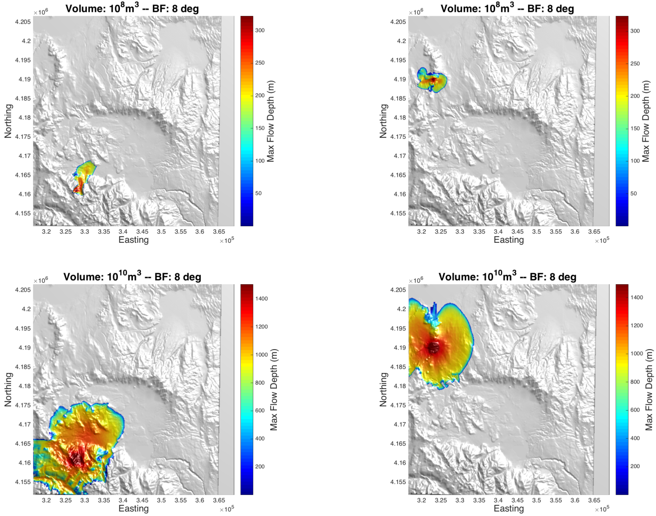
Pyroclastic flow simulation

TITAN2D

- Developed by Geophysical Mass Flow Group at the University at Buffalo (NY).[Pitman, 2003; Patra, 2005]
- Physical simulator of pyroclastic and block-and-ash flows due to volcanic activities
- Solve a system of PDE describing a depth-average model for granular flow governed by friction interaction.
- **Inputs:** vent location coordinates, flow volume, basal friction angle, internal friction angle, orientation, initial velocity, digital elevation map
- **Outputs:** flow depth, kinetic energy and flow speed at every time step at every location on the DEM

Pyroclastic flow simulation

TITAN2D

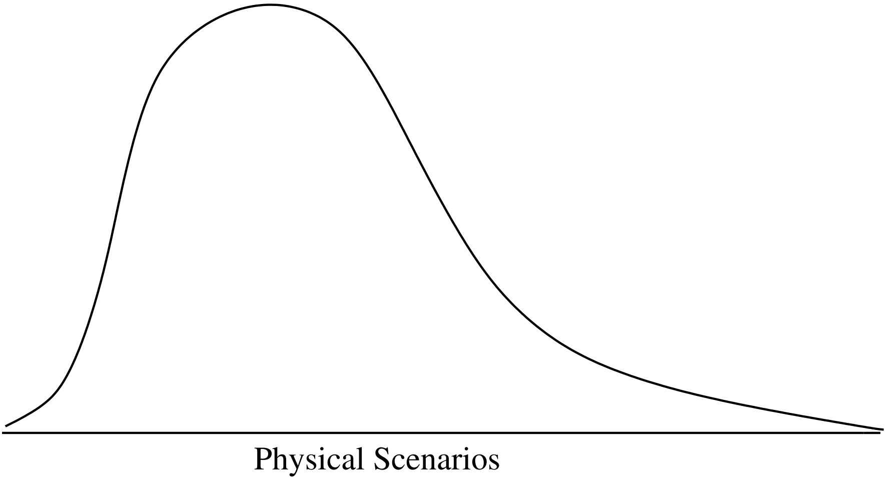


Probabilistic Inundation Map

Introduction

- Computing probabilities of inundation is prohibitively expensive requiring thousands of Monte Carlo samples, each corresponding to a run of TITAN2D
- Such an approach requires an a priori choice of input/scenario statistical model

Cartoon f(scenario)



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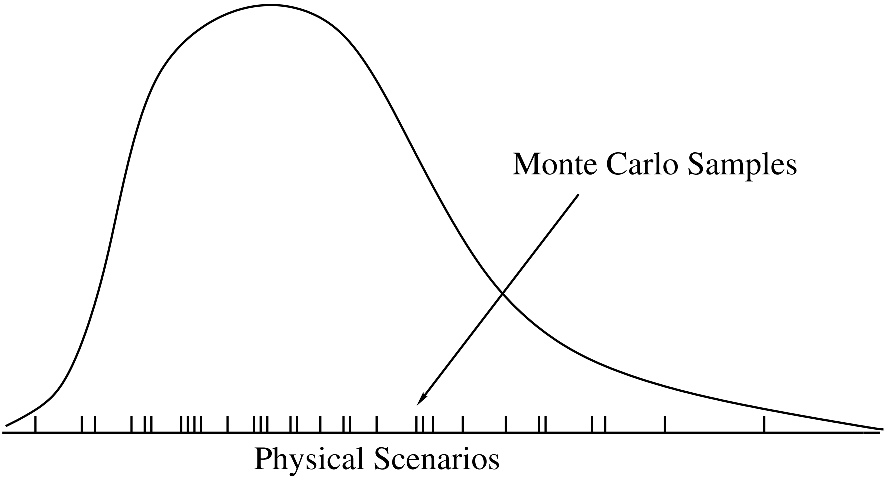

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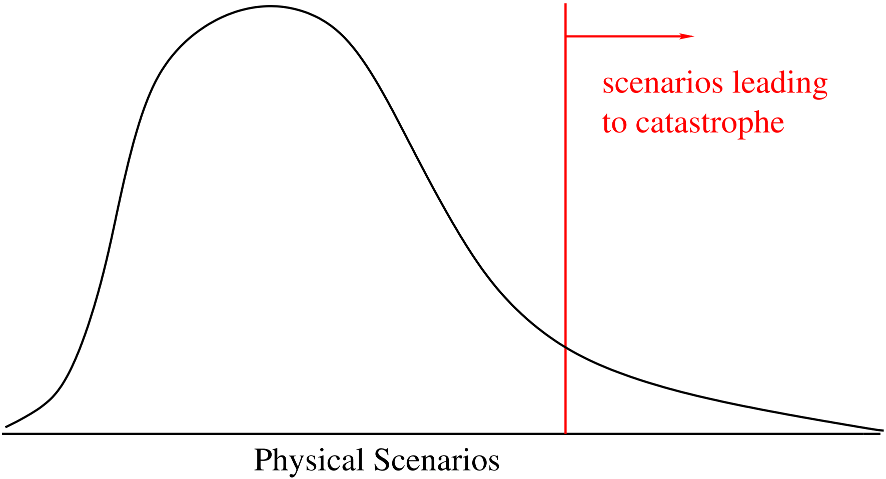

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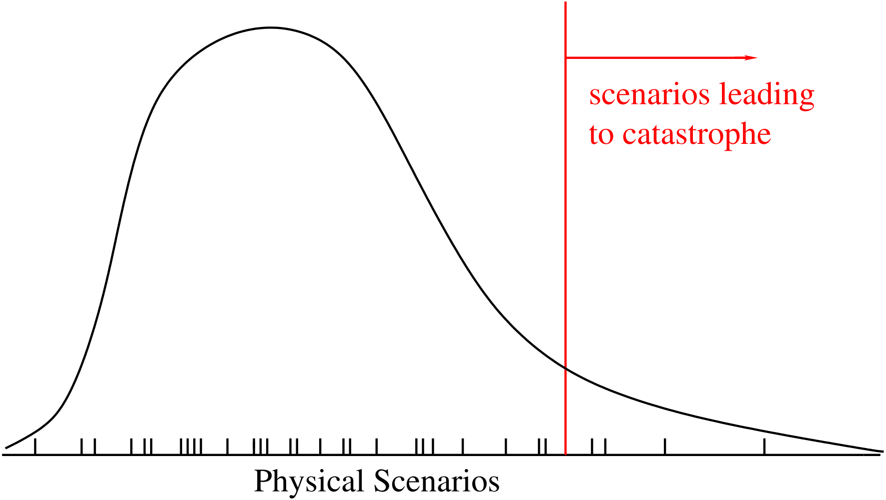

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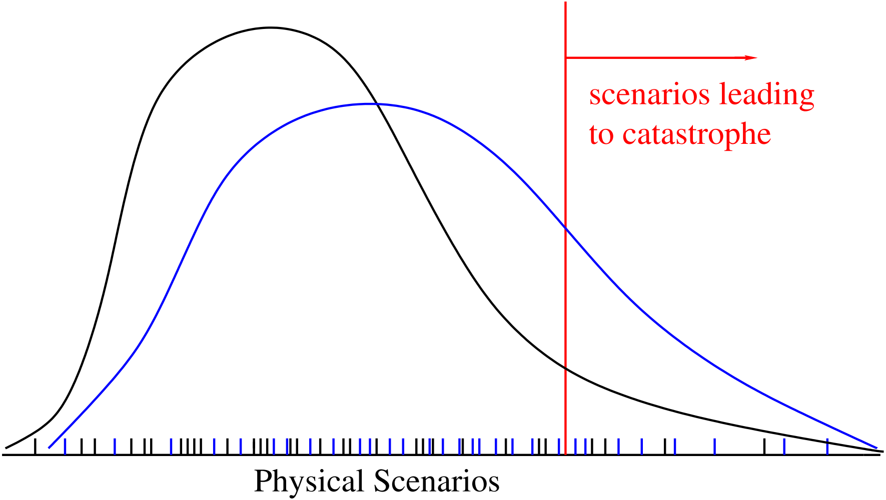

Probabilistic Inundation Map

Introduction

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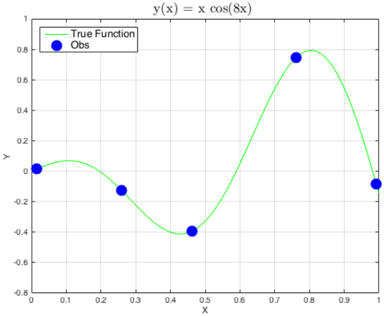
Using GaSP models and TITAN2D (input: Easting, Northing, Volume, Basal Friction angle; output: Flow depth)

- Develop a workflow for fast computation of probabilities of inundation of any location
- Graphically represent these probabilities over a map of the Long Valley

Probabilistic Inundation Map Creation

Gaussian Response Surface Models – GaSP



Probabilistic Inundation Map Creation

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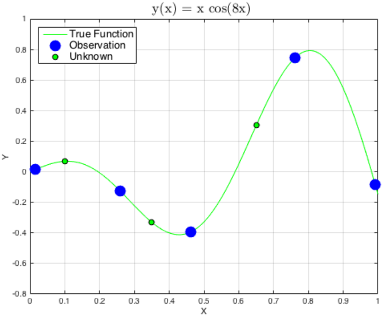
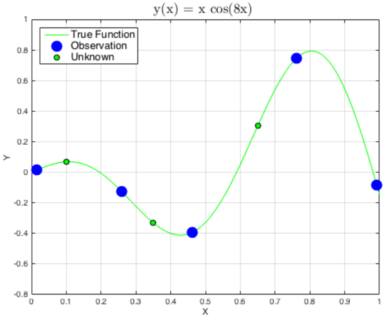


- Build statistical model of physical model output

Probabilistic Inundation Map Creation

Gaussian Response Surface Models – GaSP



- Build statistical model of physical model output
- Treat simulator "observations" as draws from a random process

Probabilistic Inundation Map Creation

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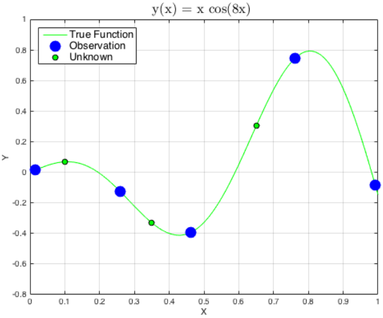

- Build statistical model of physical model output
- Treat simulator "observations" as draws from a random process
- Approximate expensive simulation with "free" random function evaluation

Probabilistic Inundation Map Creation

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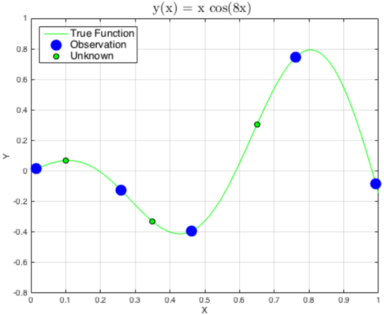


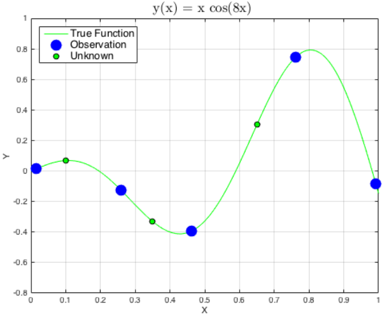
$$y(x) = \mu + \mathbf{z}(x)$$

$\mu(x) \sim f(x)$ or constant

$z(x) \sim N(0, {\sigma_z}^2 K)$

Probabilistic Inundation Map Creation

Gaussian Response Surface Models – GaSP



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$$K(x_i, x_j) = \exp\left[-\left(\frac{x_i - x_j}{\beta}\right)^2\right]$$

Probabilistic Inundation Map Creation

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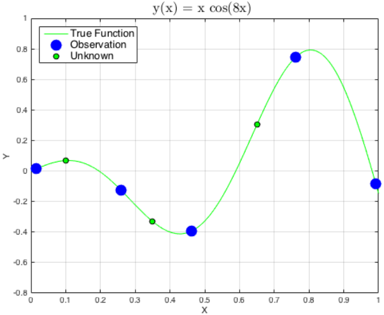

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$$\text{if } \mu = 0, \quad \begin{bmatrix} \mathbf{y} \\ y^* \end{bmatrix} \sim \mathcal{N}\left(\mathbf{0}, \begin{bmatrix} K & K_*^T \\ K_* & K_{**} \end{bmatrix}\right)$$

where $K = K(\mathbf{x}, \mathbf{x})$, $K_* = K(\mathbf{x}, x^*)$, and $K_{**} = K(x^*, x^*)$

Probabilistic Inundation Map Creation

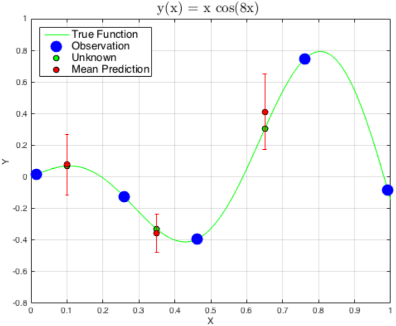
Background: Gaussian Response Surface Models – GaSP

$$y^*|\mathbf{y} \sim \mathcal{N}(\underbrace{K_* K^{-1}\mathbf{y}}_{\text{mean}}, \underbrace{\sigma_z^2(K_{**} - K_* K^{-1} K_*^T)}_{\text{variance}})$$

where β, σ_z are replaced by estimates

Probabilistic Inundation Map Creation

Background: Gaussian Response Surface Models – GaSP



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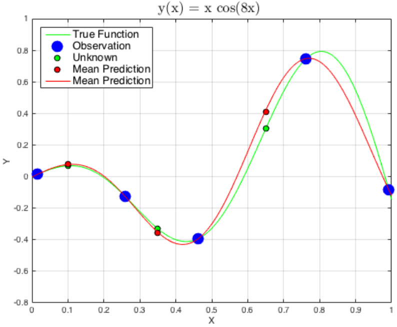

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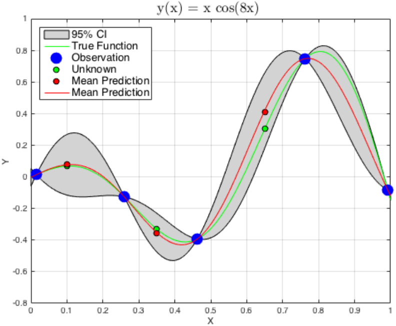

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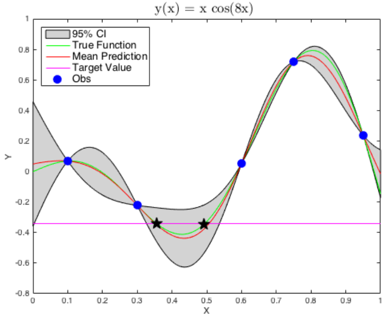
Emulator for inverse problem

Given a few simulation runs

- Fit Gaussian surface response over set of simulation inputs/outputs
- Predict simulation output at untried inputs
- Extract contour set corresponding to a particular "critical height"

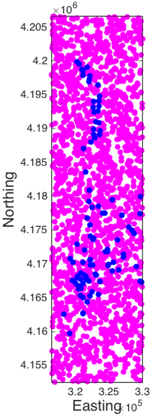


Probabilistic Inundation Map

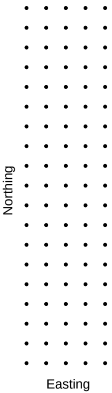
Algorithm

Run TITAN2D simulations with set of broad set of inputs (Vol, E, N). Save max-height of each simulation at location L_i

(E, N) inputs:



output locations L_i :



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Run TITAN2D simulations with set of broad set of inputs (Vol, E, N). Save max-height of each simulation at location L_i

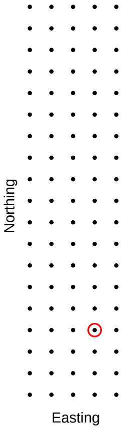
for each location L_i in parallel **do**

    Fit GaSP emulator over TITAN2D input/output

    Evaluate GaSP over a 3-D input space grid

    Extract level surface of critical flow height

end for



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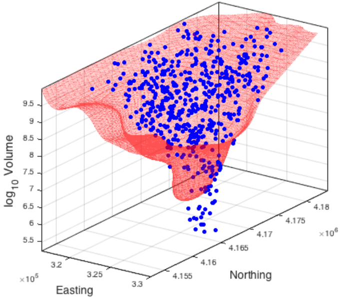
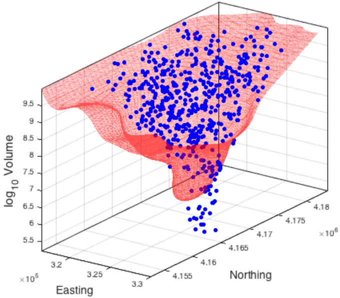


Figure: 3-D 1 meter level surface for the Town of Mammoth Lakes (CA) (in red) and TITAN2D input (in blue)

Probabilistic Inundation Map

Algorithm



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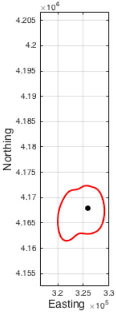


Figure: 1 meter contour corresponding to Volume $= 10^8 m^3$

Probabilistic Inundation Map

Algorithm

Run TITAN2D simulations with set of broad set of inputs (Vol, E, N). Save max-height of each simulation at location L_i

for each location L_i in LV in parallel **do**
    Fit GaSP emulator over TITAN2D input/output
    Evaluate GaSP over a 3-D input space grid
    Extract level surface corresponding to critical flow height
    Compute probability of inundation (conditioned on volume)
end for

Probability calculations

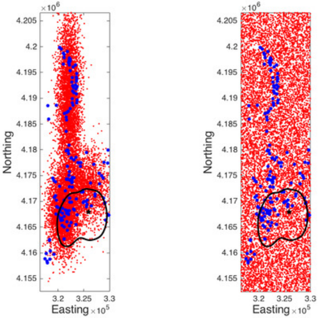
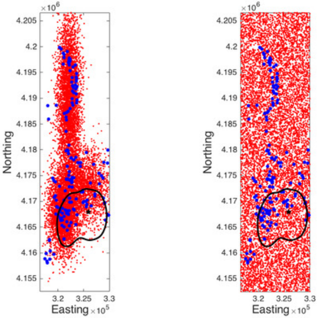


Figure: Two models of vent location used to compute the probability of inundation of the Town of Mammoth Lakes (CA) given an event of Volume = 100 M m^3

Probability calculations



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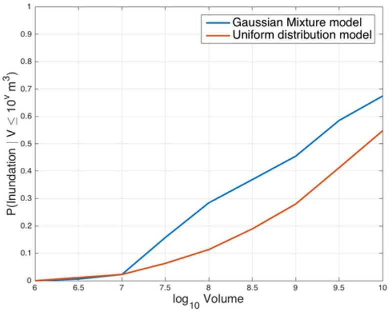


Figure: Probability profile curves for the town of Mammoth Lakes (CA), under different model of vent locations.

Probabilistic Hazard Maps P(inundation | $V = 100$ M m^3)

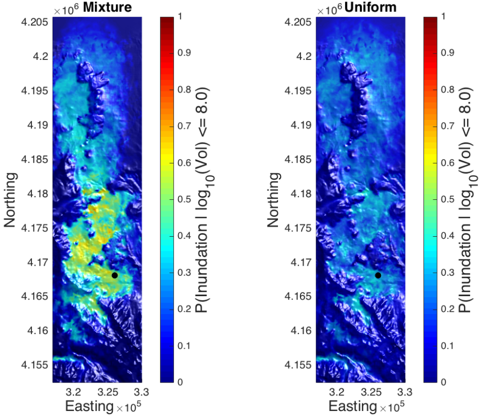
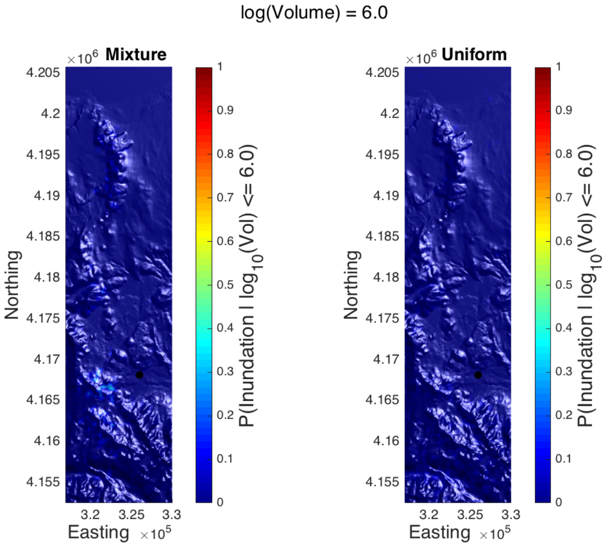


Figure: Volume = 100 M m^3

Probabilistic Hazard Maps



Looking forward

Short term:

- Use more sophisticated vent opening maps at LV [Bevilaqua, 2017]

Medium term

- Use model of frequency-volume for 100-year probabilistic hazard maps

$$P(\text{catastrophe within } t \text{ years} \mid \text{scenario model}) = 1 - \exp(-\lambda t P(\text{catastrophe} \mid \text{scenario model}))$$

Flexible framework

- Not specific to hazard threat (pyroclastic flow) OR physical model computation (TITAN2D) OR volcano
- Can be used for emerging or on-going volcanic activity
  details in [Spiller SIAM JUQ, 2014] [Bayarri IJUQ, 2015]
- Can be used for short term forecasting – no need to assume stationarity in scenario models [Wolpert (to be submitted soon), 2017]

Acknowledgments

- Thank you!
- NSF Grants SES 1521855, DMS 1228265, EAR 1331353