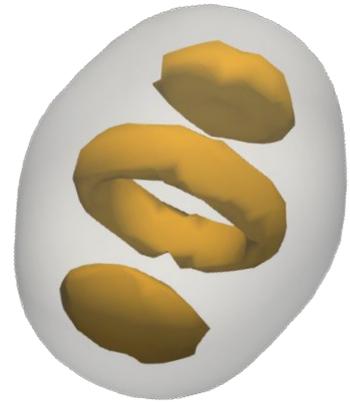
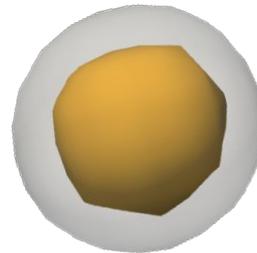


# Uncertainty quantification for low-energy heavy-ion reactions

Kyle Godbey

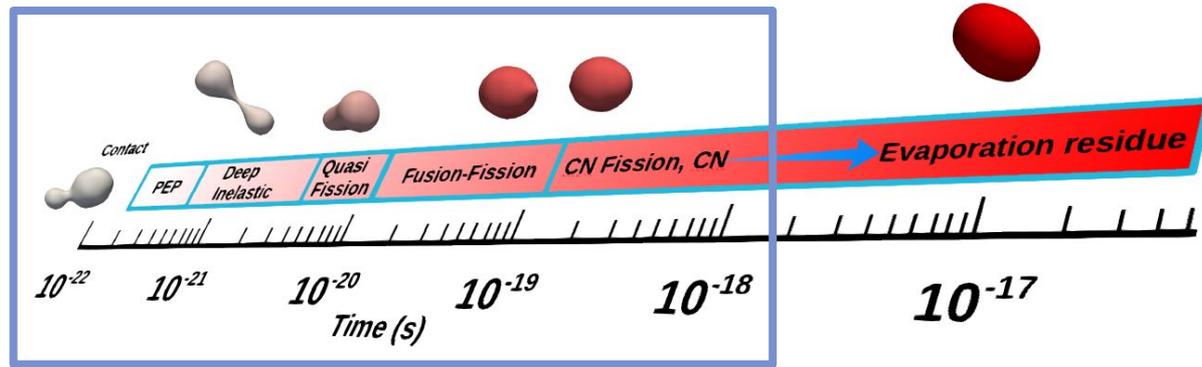


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# Our lens? Real-Time Dynamics

Time-dependent, microscopic theories offer a rich depiction of the many complicated things nuclei might do during a reaction



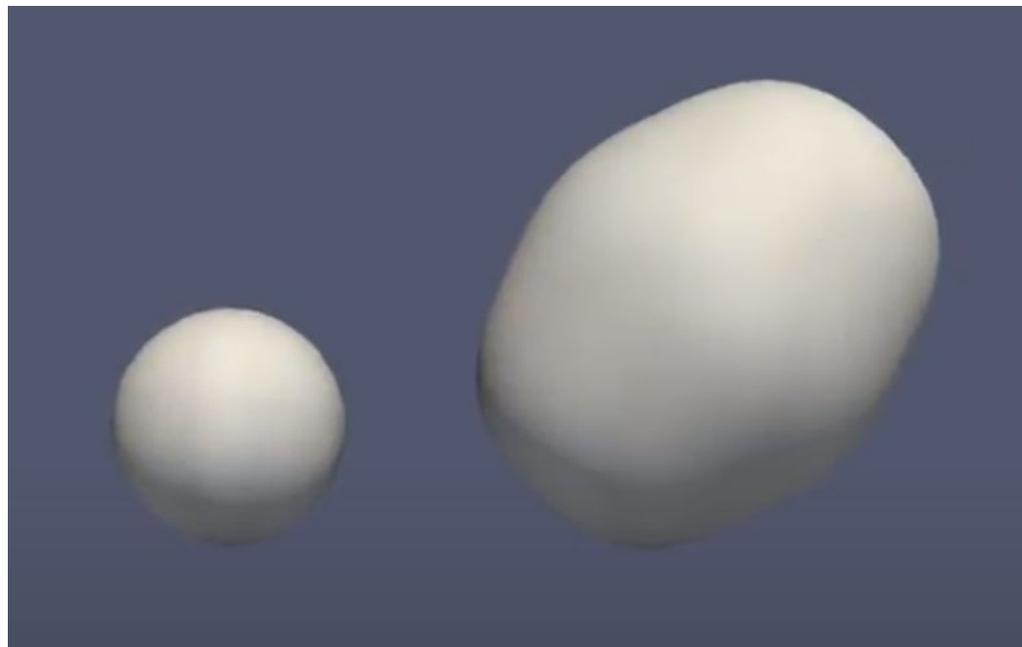
# The framework: Density Functional Theory

'Microscopic' method optimized for description of one-body observables

Fantastically extensible framework to go beyond base assumptions



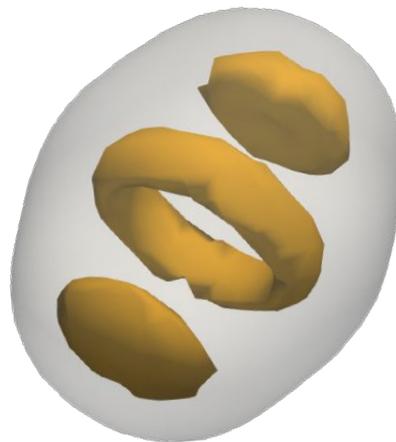
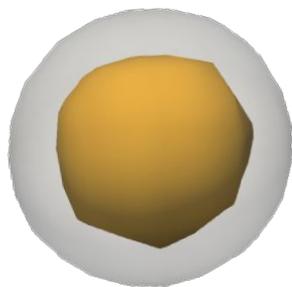
# Features of DFT: Structure



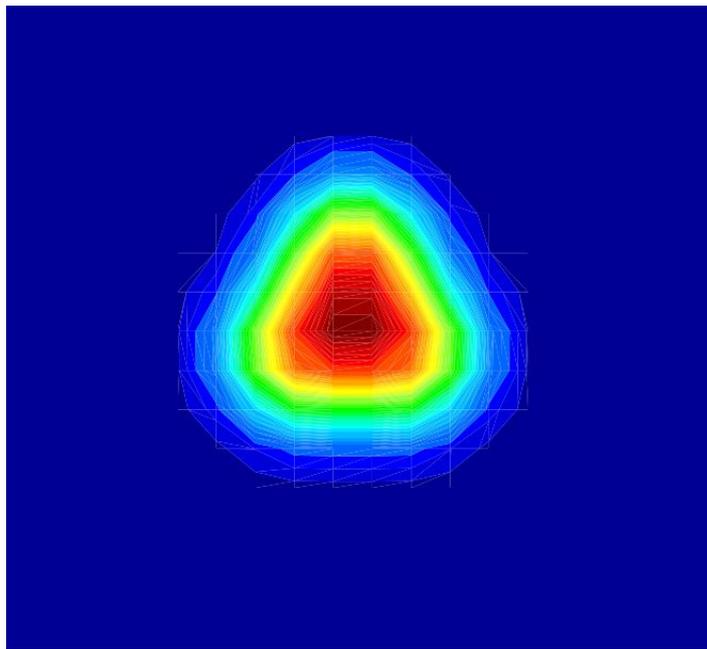
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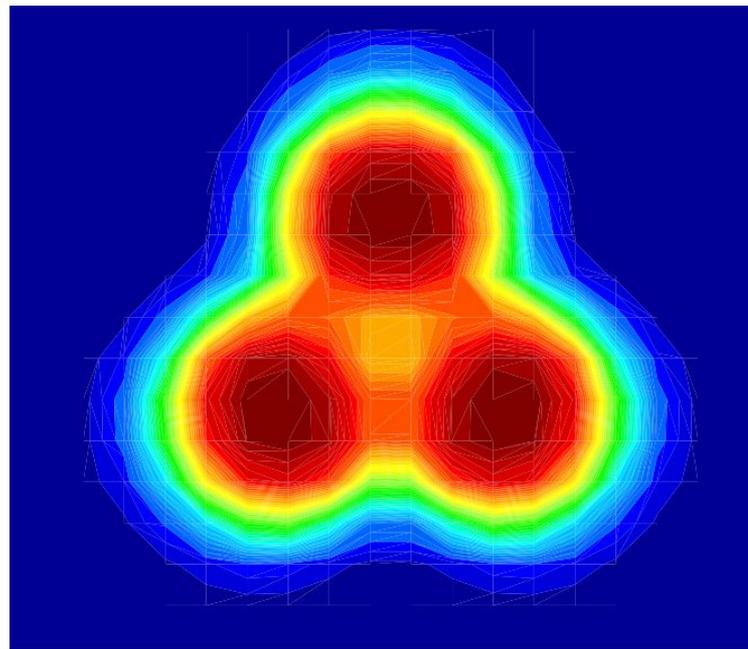
# Features of DFT: Structure



# Features of DFT: Structure



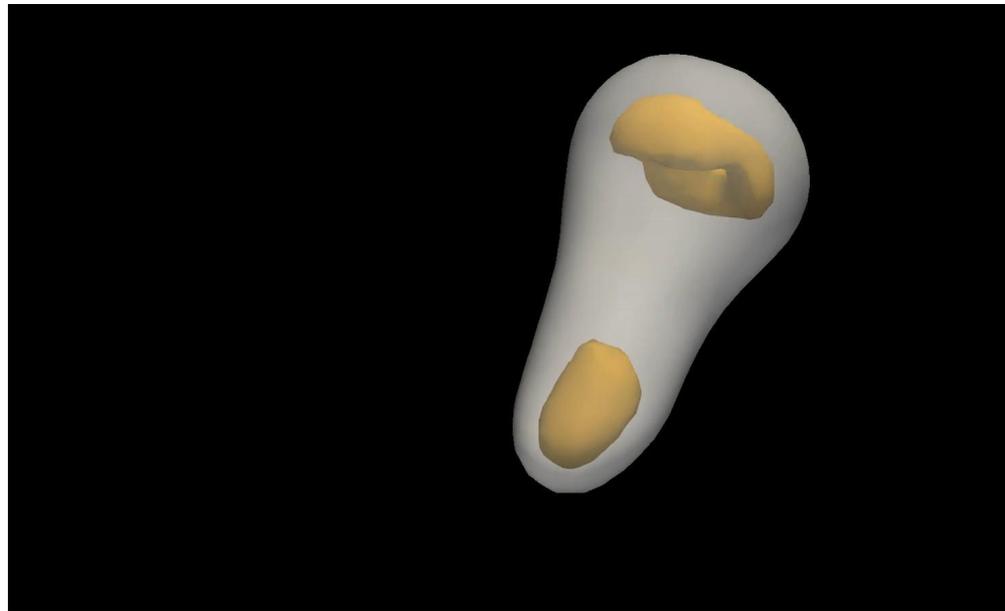
Density,  $\rho(r)$



Nucleon localization function



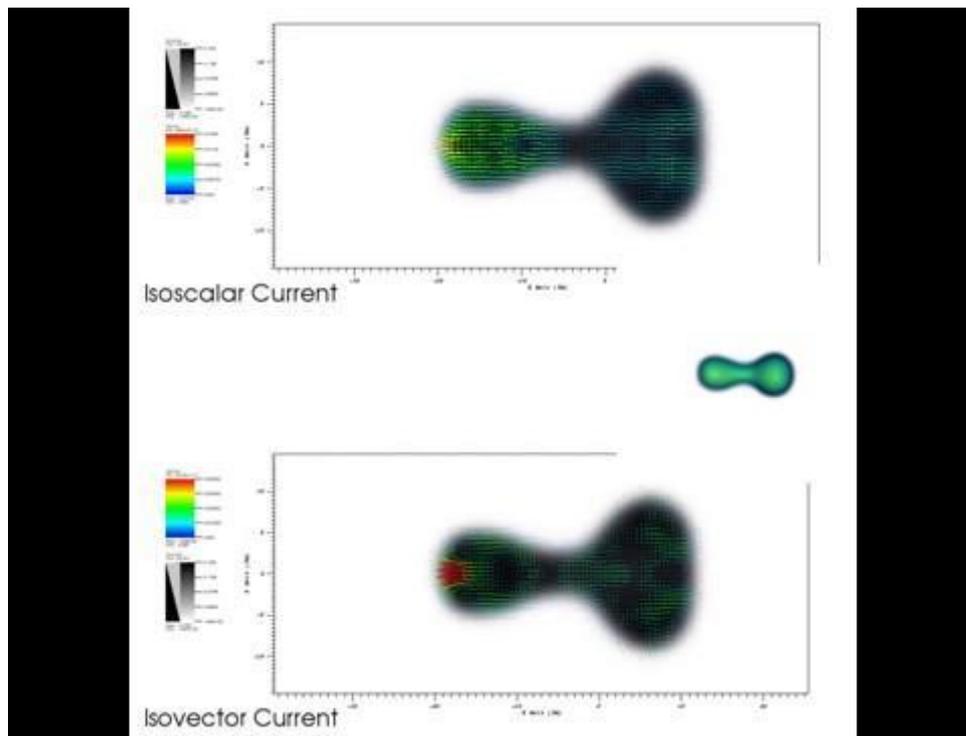
# Features of DFT: Dynamics



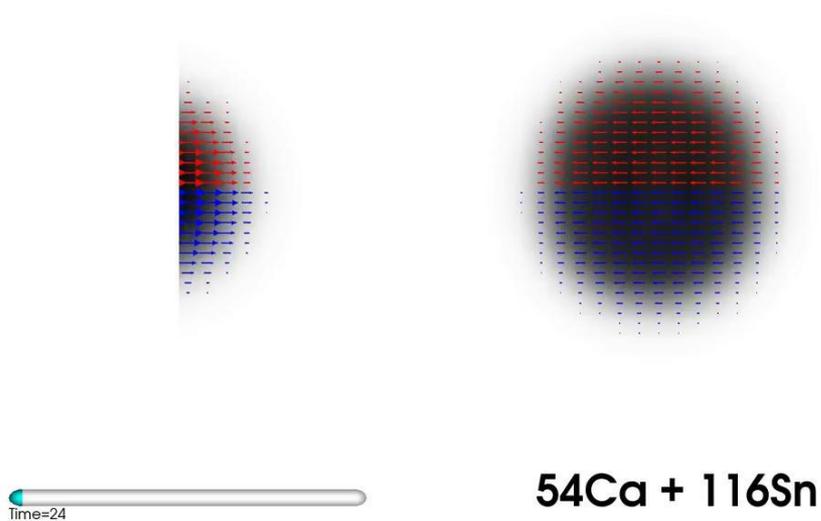
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# Features of DFT: Dynamics

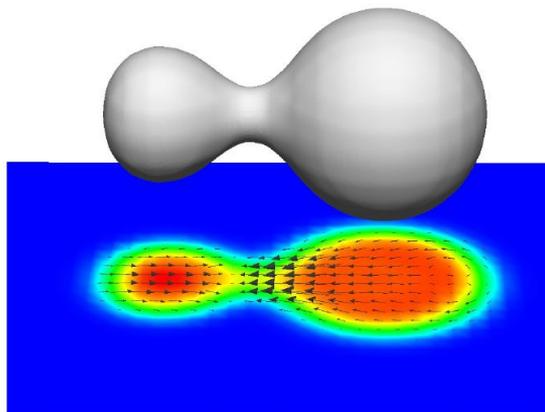


# Features of DFT: Dynamics



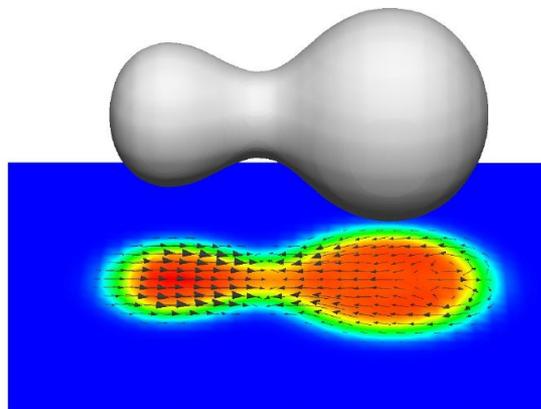
# Features of DFT: Dynamics

$40\text{Ca} + 132\text{Sn}$



transfer

$48\text{Ca} + 132\text{Sn}$



No net transfer



# What Drives the Dynamics (and Structure)?

The energy density functional! A functional of various densities and currents that defines the system

e.g.

$$\mathcal{H}_I(\mathbf{r}) = C_I^p \rho_I^2 + C_I^s \mathbf{s}_I^2 + C_I^{\Delta\rho} \rho_I \Delta\rho_I + C_I^{\Delta s} \mathbf{s}_I \cdot \Delta\mathbf{s}_I + C_I^{\tau} (\rho_I \boldsymbol{\tau}_I - \mathbf{j}_I^2) + C_I^T (\mathbf{s}_I \cdot \mathbf{T}_I - \hat{J}_I^2) + C_I^{\nabla J} (\rho_I \nabla \cdot \mathbf{J}_I + \mathbf{s}_I \cdot (\nabla \times \mathbf{j}_I))$$



# Parameter Determination

One method is, given an EDF, fit the constants to some experimental data

The result? Many, many, many 'forces' for a given functional. Some fave Skyrme-types include SkM\*, SLy4d, SLy5t, SV-Min, UNEDF1, etc.



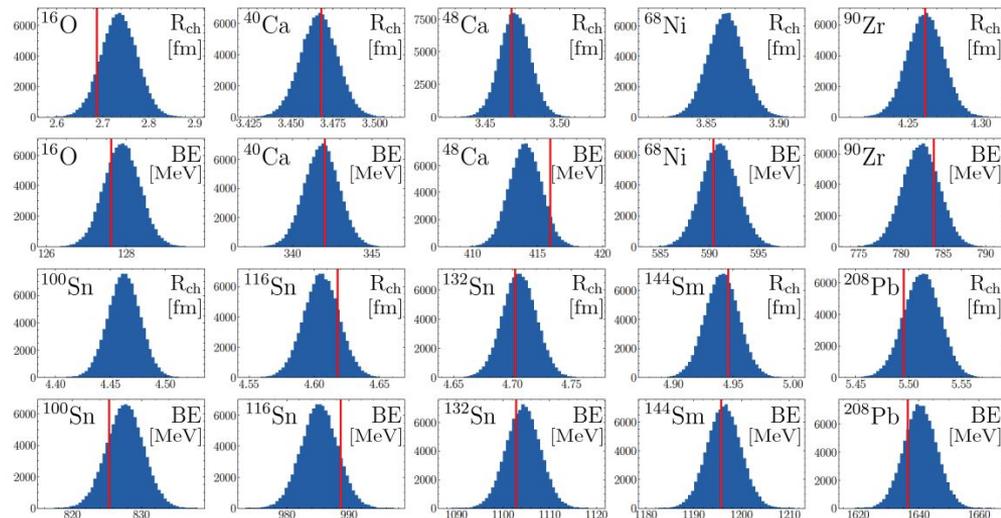
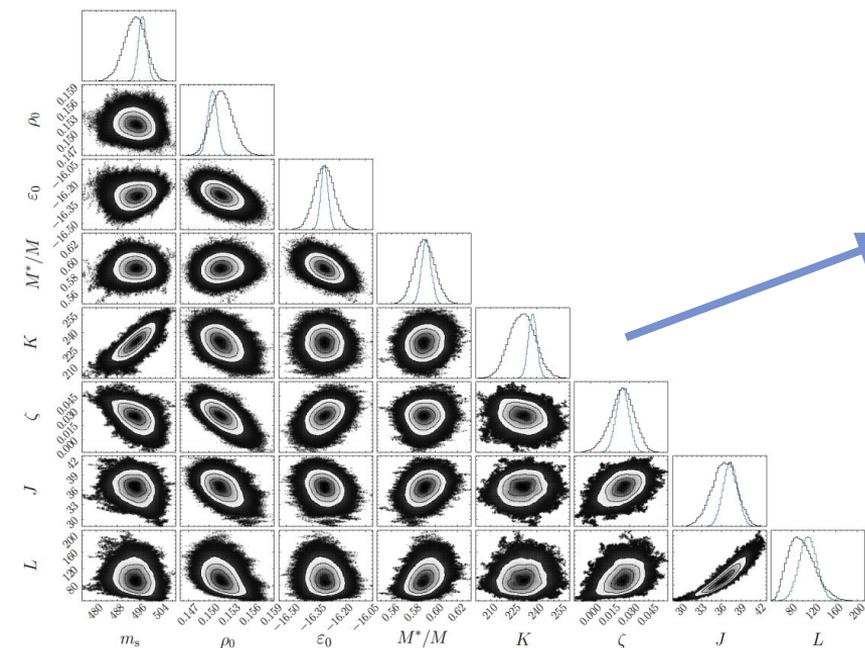
# Parameter Determination

But.. nobody is perfect, sorry SLY4d. Given a certain set of data there is some uncertainty on what the optimal parameters are

So why do we even need optimal parameters? Instead we can define our physical model as a distribution of reasonable parameters



# “Doing UQ”



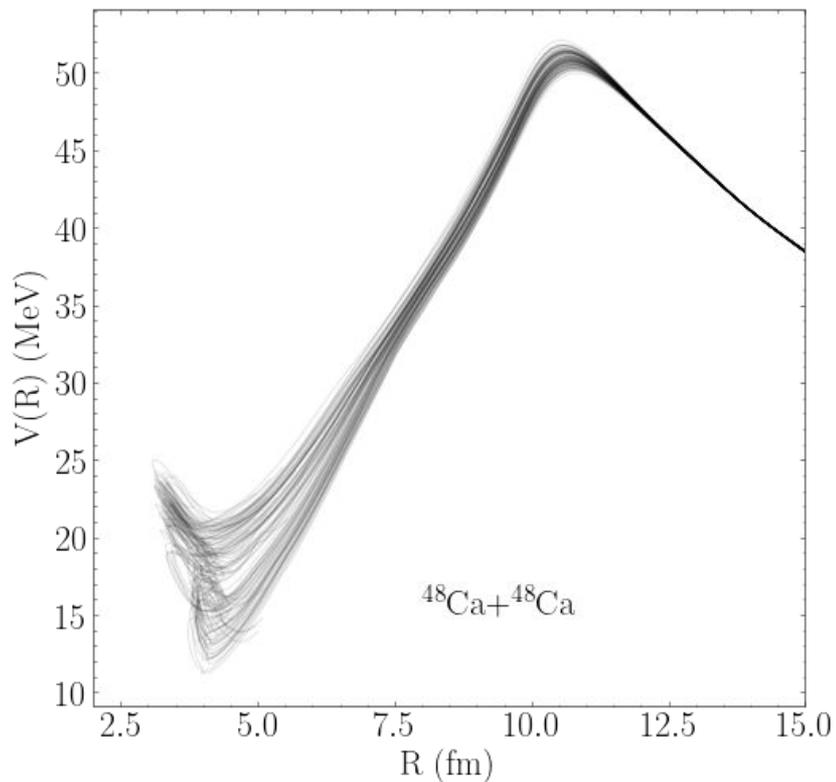
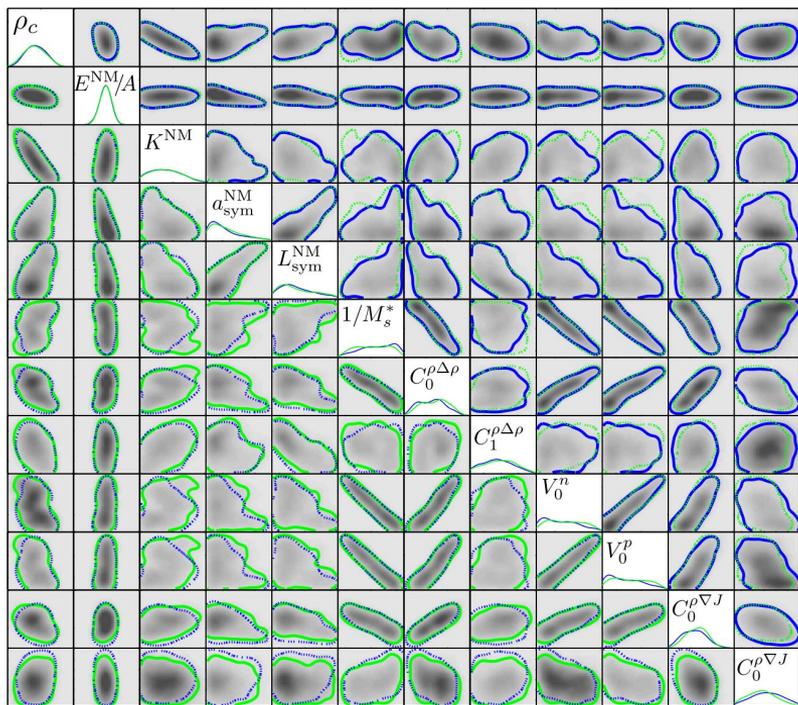
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Image Credit:

P Giuliani, **K Godbey**, E Bonilla, F Viens, J Piekarewicz, Bayes goes fast: Uncertainty Quantification for a Covariant Energy Density Functional emulated by the Reduced Basis Method

# “Doing UQ”



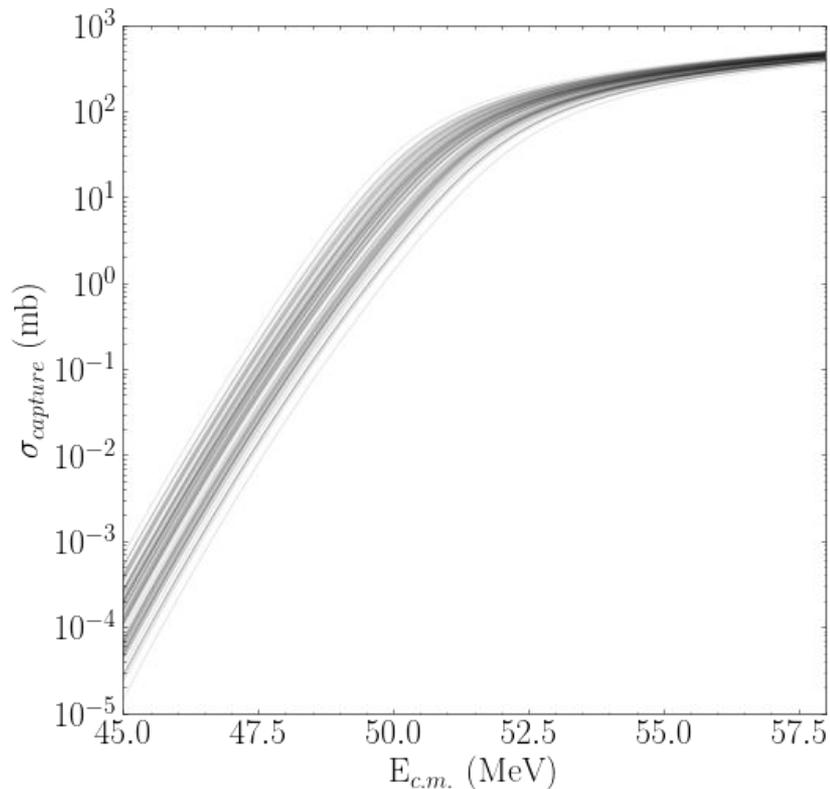
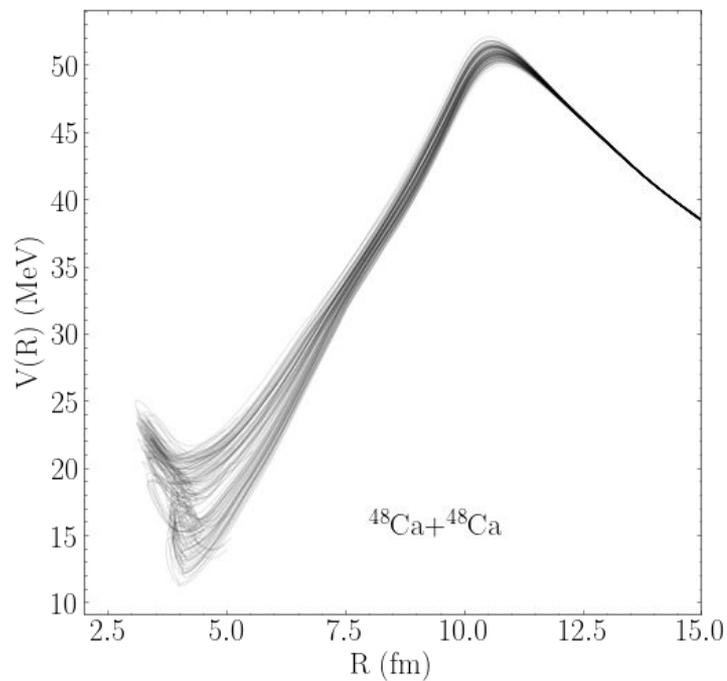
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Image Credit:

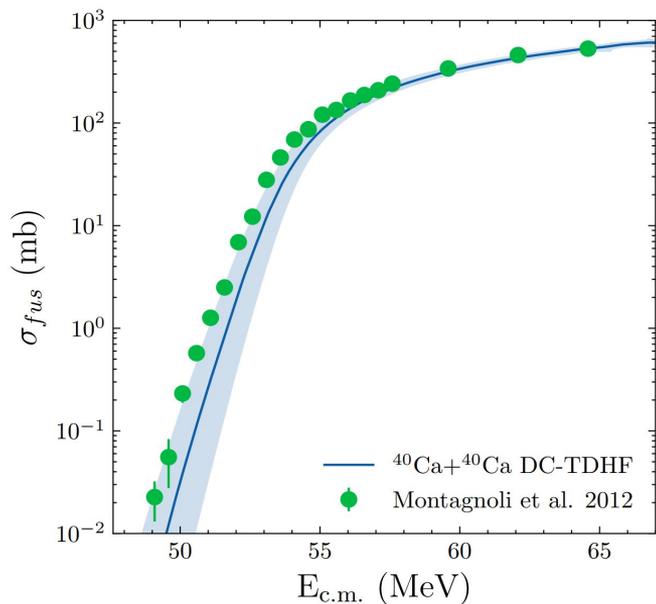
J. D. McDonnell, N. Schunck, D. Higdon, J. Sarich, S. M. Wild, and W. Nazarewicz,  
Uncertainty Quantification for Nuclear Density Functional Theory and Information Content  
of New Measurements, Phys. Rev. Lett.114, 122501 (2015).

# “Doing UQ”

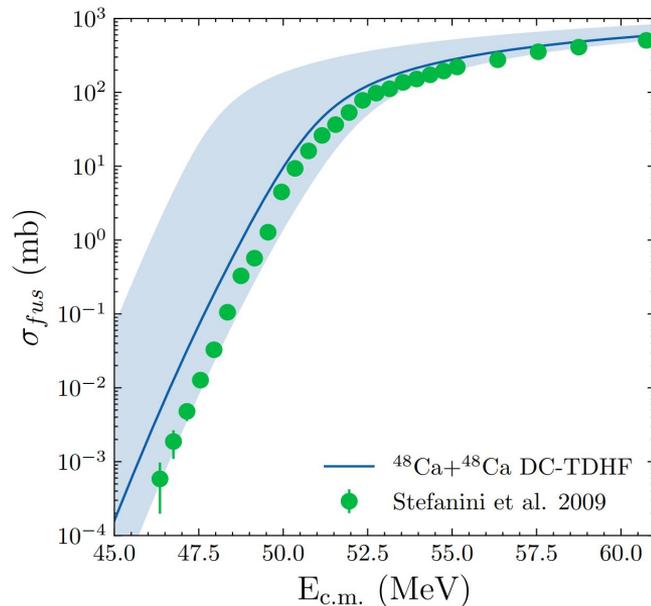


# “Doing UQ”

$^{40}\text{Ca} + ^{40}\text{Ca}$



$^{48}\text{Ca} + ^{48}\text{Ca}$



# Extracting Barrier Height

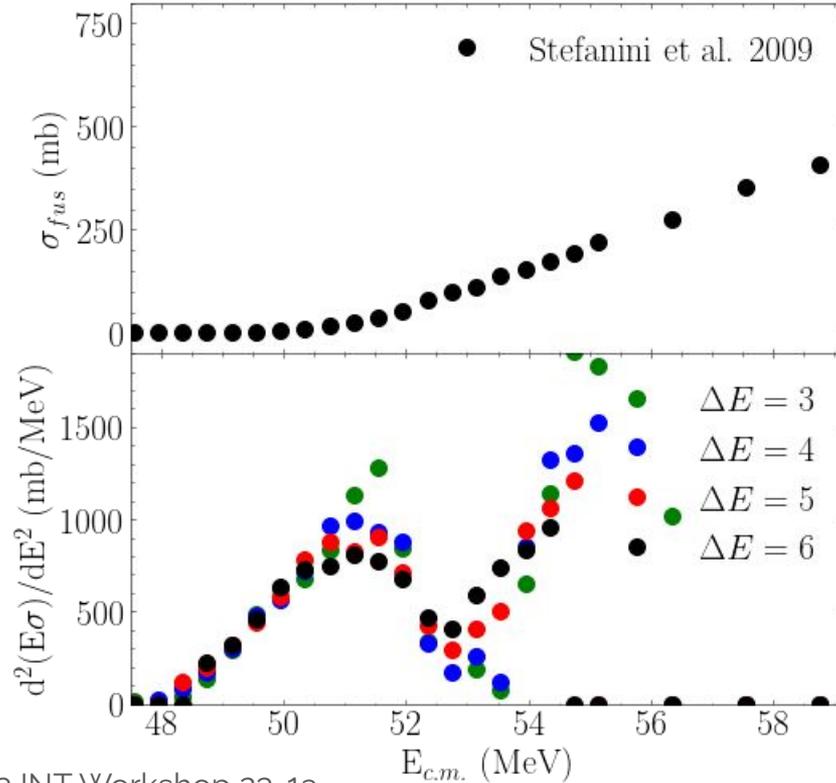
To get the barrier height from experimental data without any model dependence, we should deal only with the data

To this end, let's consider the experimental barrier distribution:

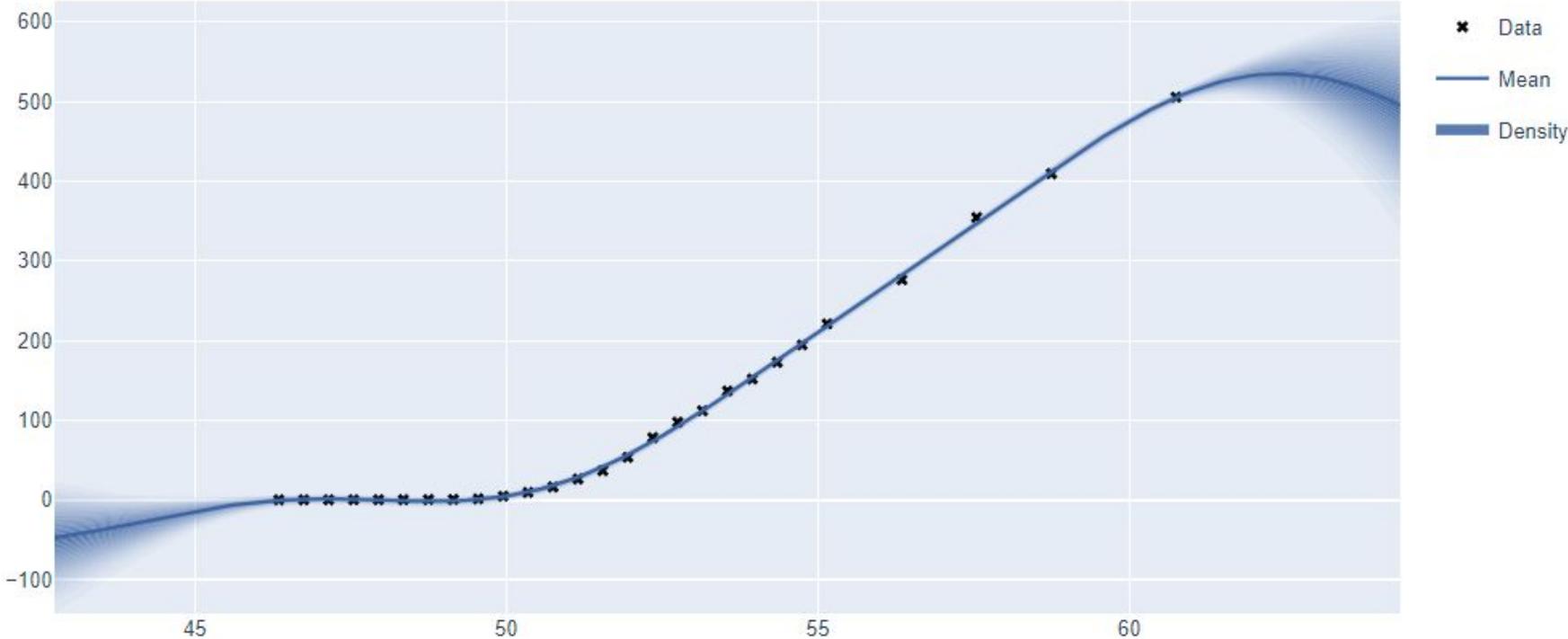
$$D_{\text{exp}}(E) = \frac{d^2(E\sigma)}{dE^2}$$



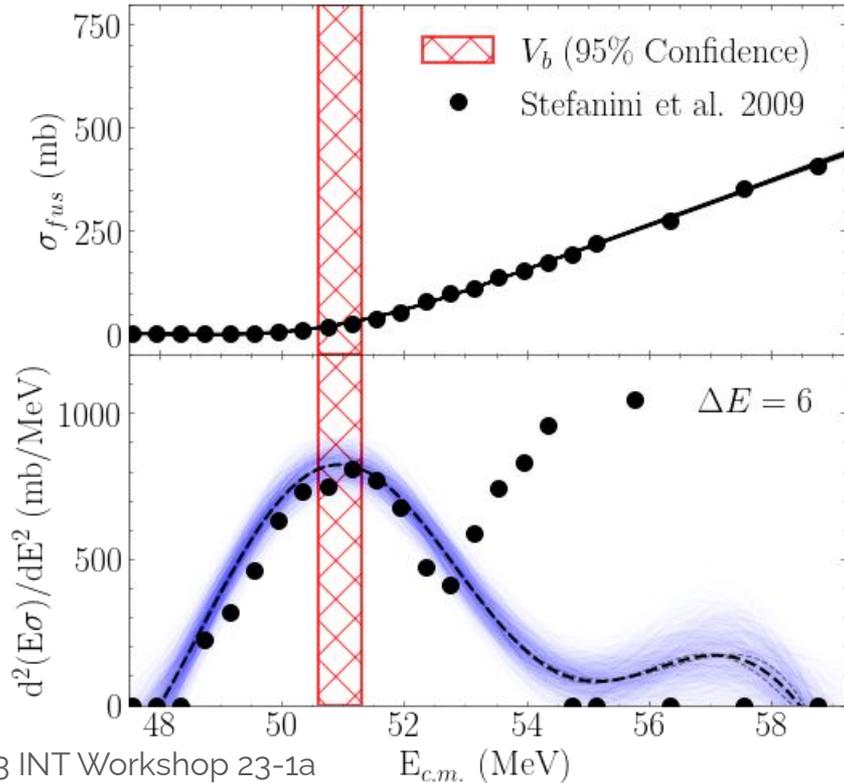
# Extracting Barrier Height



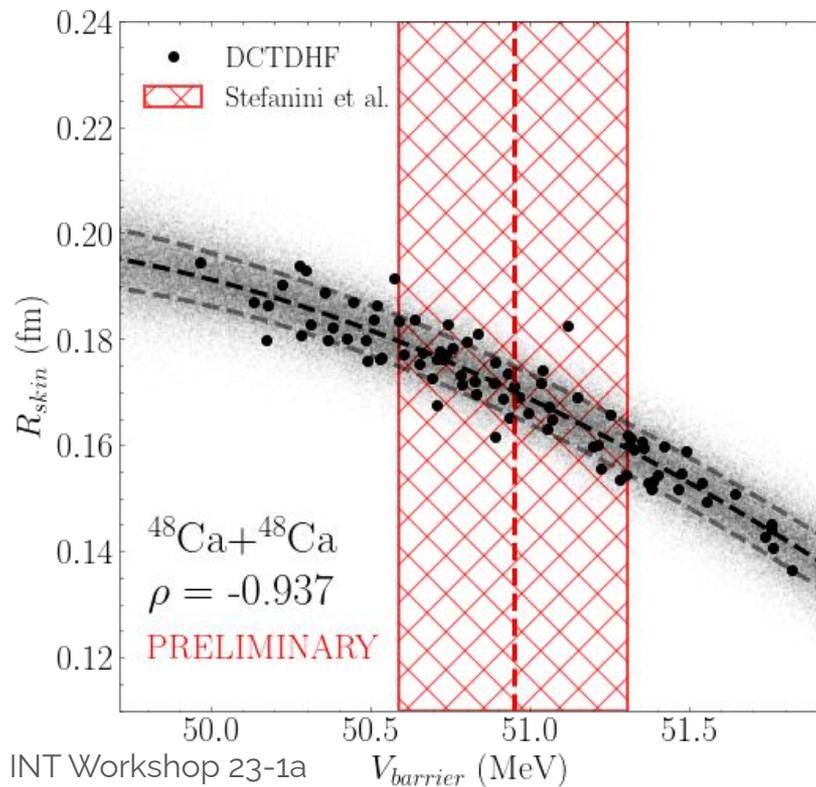
# Extracting Barrier Height



# Extracting Barrier Height



# Checking Skin vs. Barrier Correlations

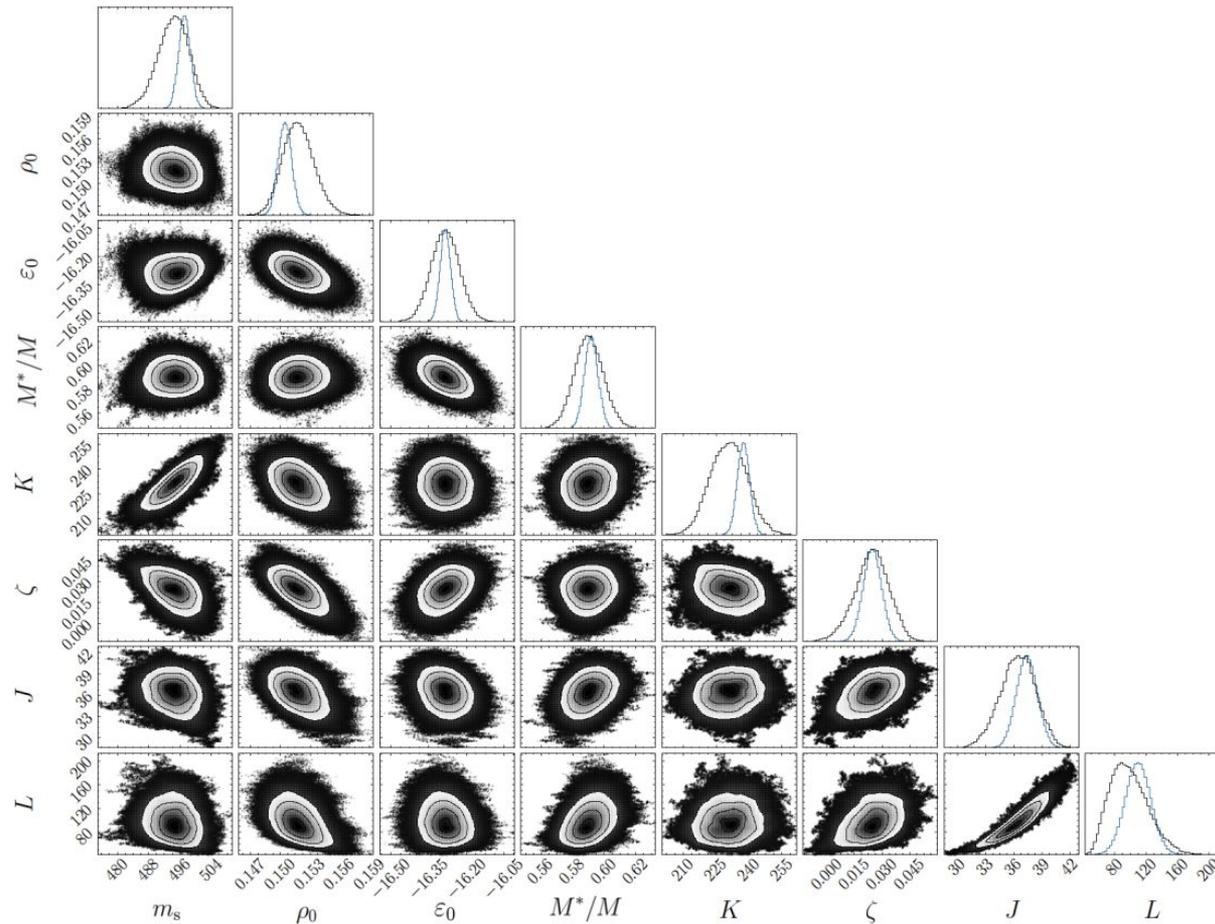


# What Next?

A strong correlation is a strong indicator of opportunity,  
and this is just one system

Constraints are great, but including fusion cross sections  
from TDDFT in a direct Bayesian calibration is unlikely  
without advances in emulation





What about RBMs?

~5,000,000 samples in  
about a day on  
commodity hardware  
for covariant DFT



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Image Credit:

P Giuliani, **K Godbey**, E Bonilla, F Viens, J Piekarewicz, Bayes goes fast: Uncertainty  
Quantification for a Covariant Energy Density Functional emulated by the Reduced Basis  
Method

# Challenges

Robust calibration requires great emulators, but we're behind on time-dependent emulation

RBM's have proven great for DFT and scattering, but generally perform worse for time evolution

Thus current direction is on data-driven approaches like neural implicit flow or Fourier neural operator



# Challenges

Even with powerful emulation, direct Bayes may still be out of reach

Techniques such as the polynomial chaos expansion (like an RBM for your random distribution) might be crucial to lower the total number of samples required



# Conclusions

Linking structure to reactions must consider the uncertainties lurking at every step, no matter the energy scale

Nuclear structure often contains lots of intricacies and possible refinements. Each of these intricacies are affected by the model uncertainties that generated them



# Immense Gratitude to All Collaborators!



## Funding

DOE NNSA Grant Nos. DE-NA0004074, DE-NA0003885

DOE Grant No. DE-SC0013365

## Computing Resources

Australian National Computational Infrastructure Raijin and Gadi

Oak Ridge Leadership Computing Facility Summit

Argonne Leadership Computing Facility Polaris

Texas A&M High Performance Research Computing Terra and Ada

Michigan State University HPCC