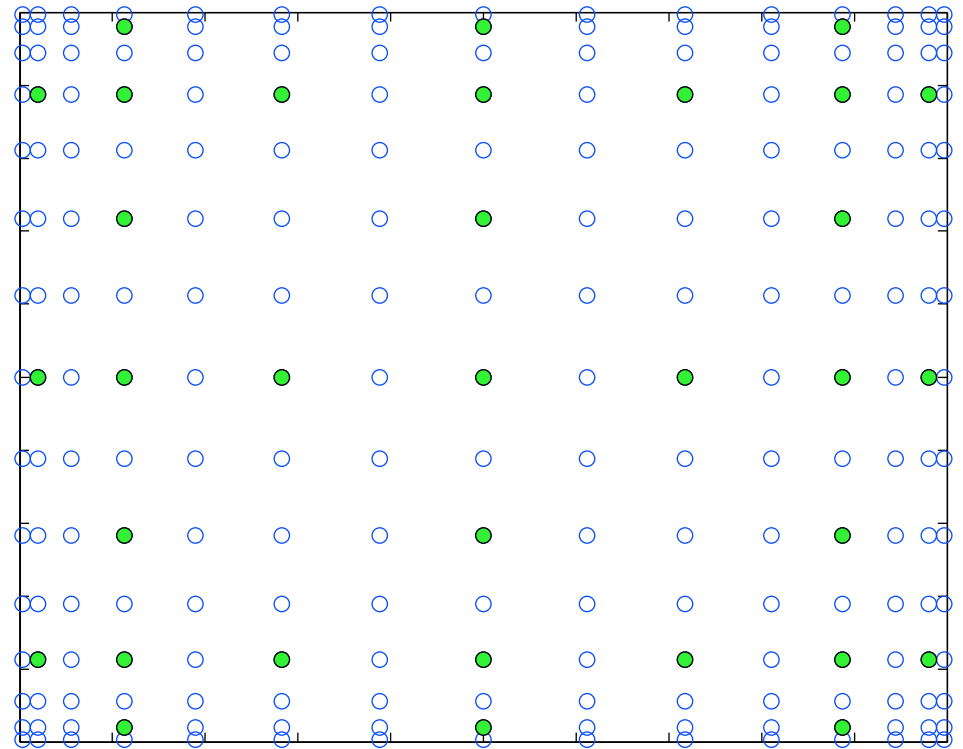


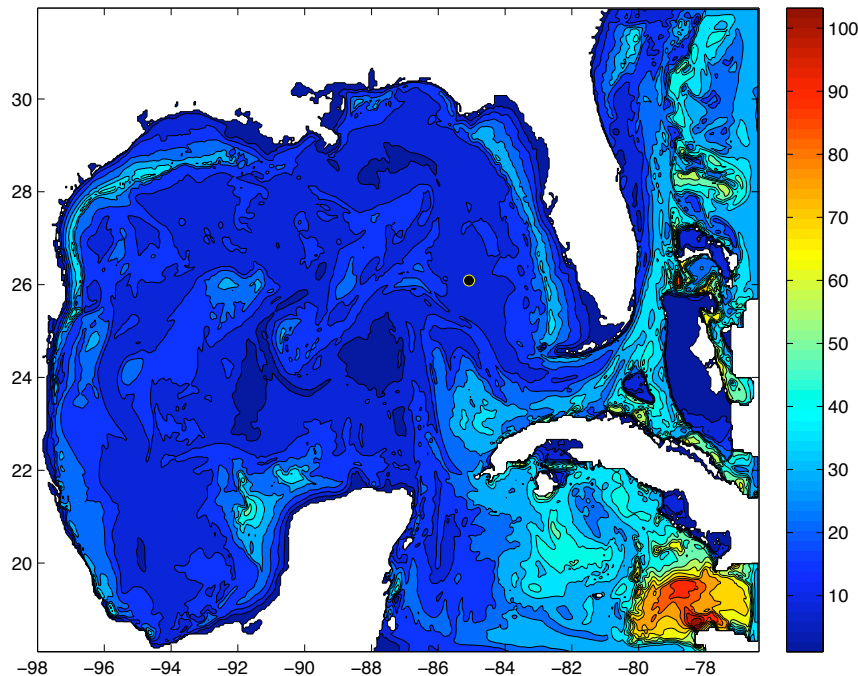
Sparse Quadratures: Motivation

- Fully tensorized quadratures are particularly prone to the so-called curse of dimensionality. With q quadrature points along each axis, one has q^N quadrature points in N dimensions.
- Sparse quadratures aim at mitigating this curse by relying on partially-tensored formulas.

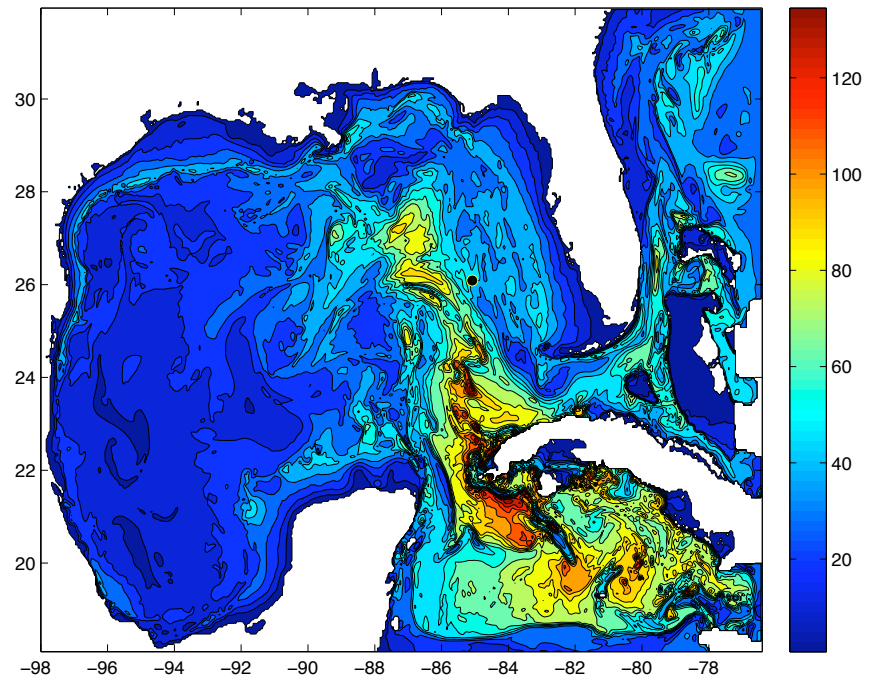


Solid – partially tensored
Hollow – full tensorization

Computational Experiment



t=69 hrs

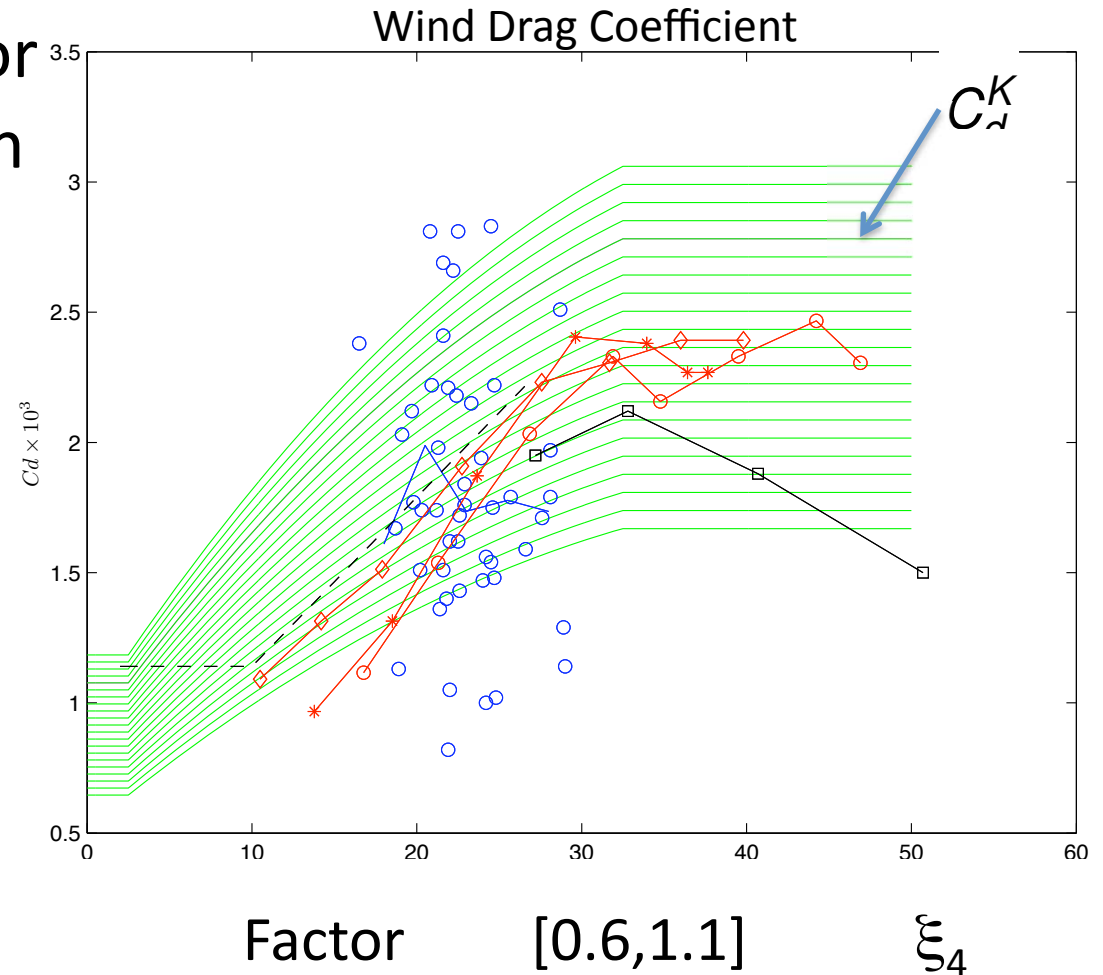


T=159 hrs

- Circulation in GOM. Analyze impact of uncertainty in (a) subgrid stress parameterization, and (b) wind coupling.
- High resolution ($1/25^\circ$) simulations. Time period: Sep 1 – 10, 2004 (t=0 corresponds to 9/1). Track of Hurricane Ivan

Input uncertainties

- Uniform distributions for mixing parameterization and wind coupling
- KPP Model
 - Richardson number $[0.1, 0.7]$ ξ_1
 - Background viscosity $[10^{-4}, 10^{-3}]$ ξ_2
 - Background diffusivity $[10^{-5}, 10^{-3}]$ ξ_3



Blue circles: aircraft (French et al., 2007); Black: drop sonds (Powell et al., 2003); Dashed: drop sonds (Powell, 1981); Red: lab data (Donelan et al., 2004); Pink Line: HYCOM (Kara et al., 2000)

Analysis

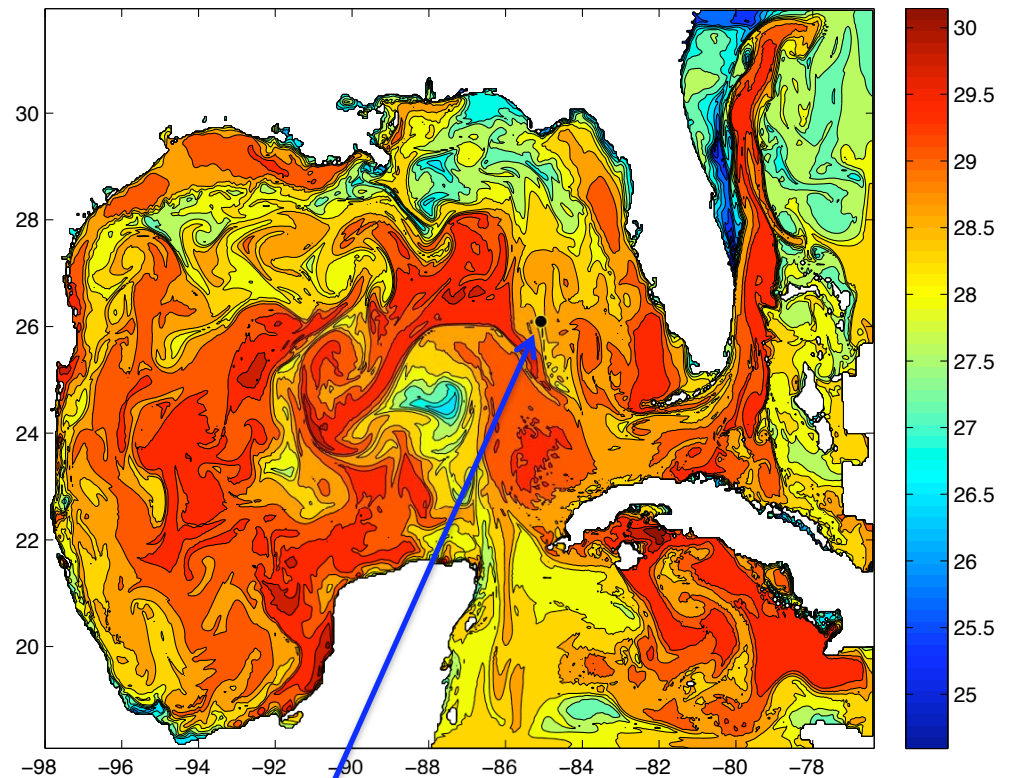
- Systematic Refinement
- 4-dimensional space

	$l=1$	$l=2$	$l=3$	$l=4$
$d=2$	5	9	17	33
$d=3$	7	19	39	87
$d=4$	9	33	81	193

193 **Nested** Realizations

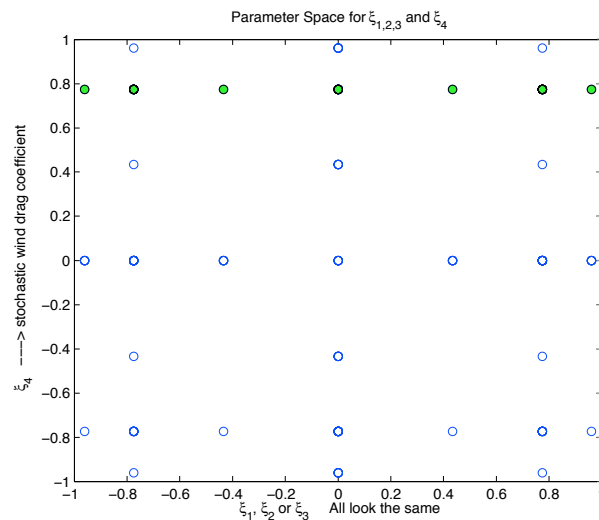
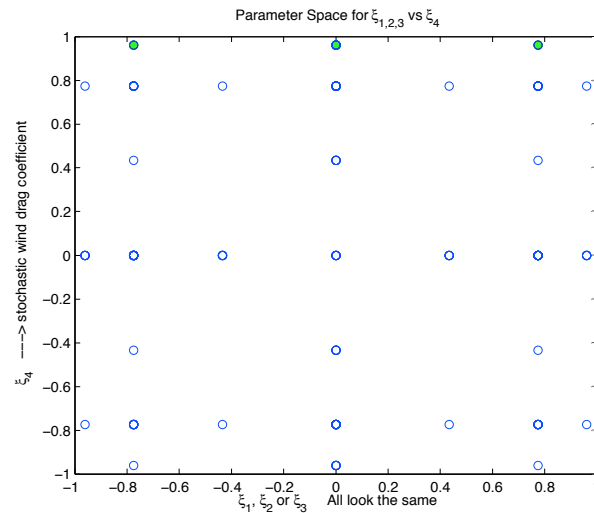
Quadrature exact up to $p=l+1$

Sea Surface Temperature (SST)

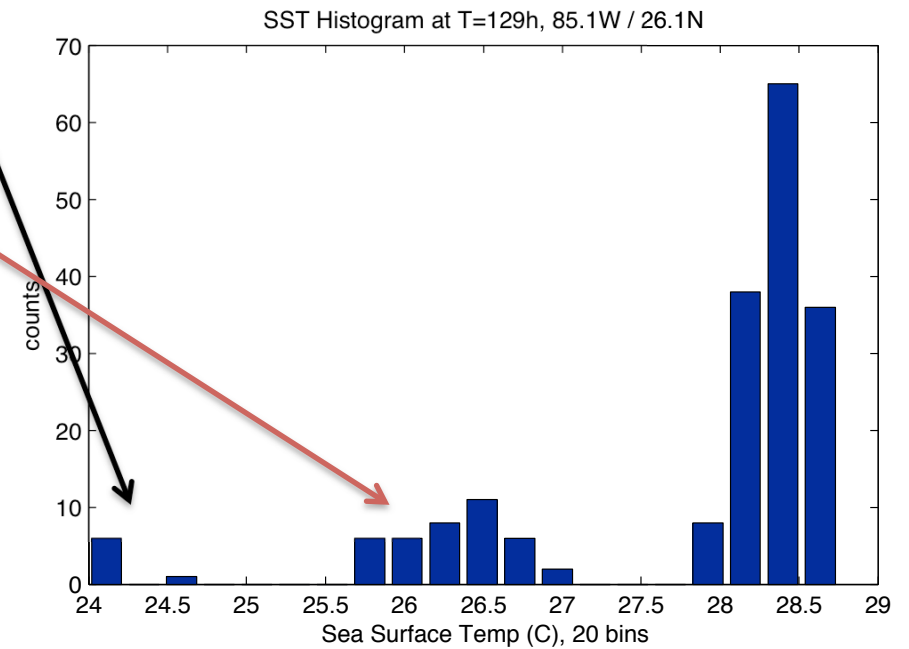
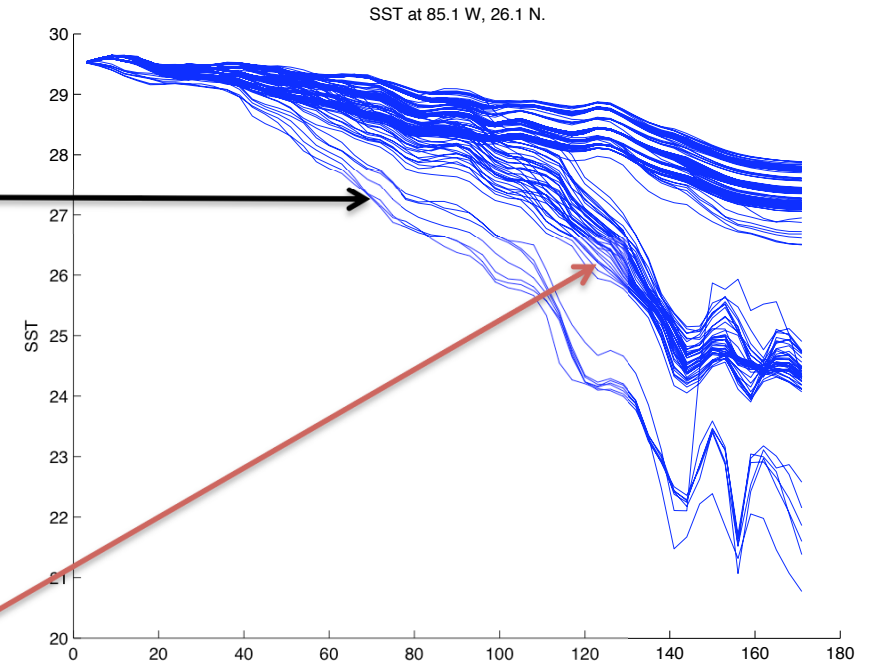


Stochastic Database

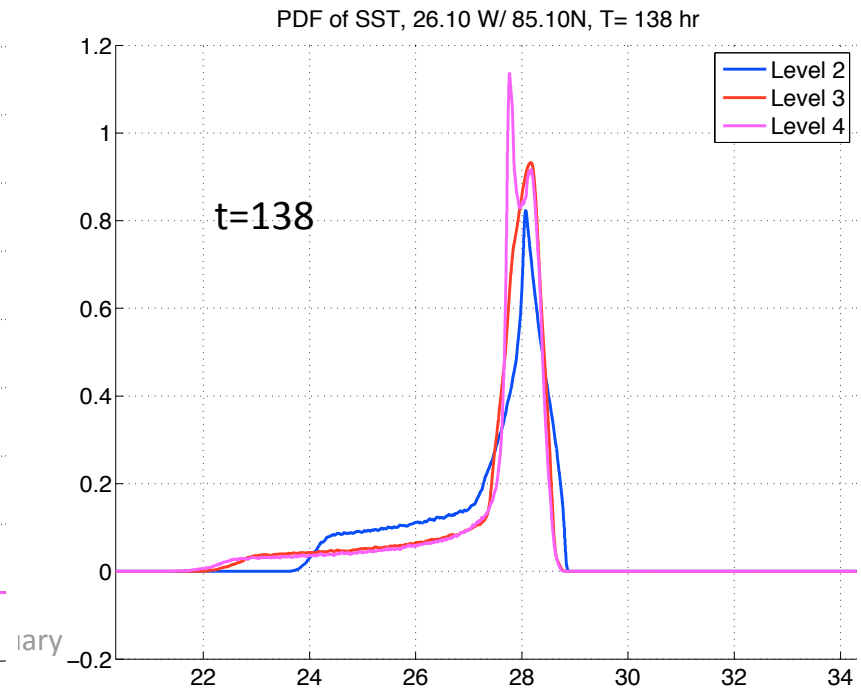
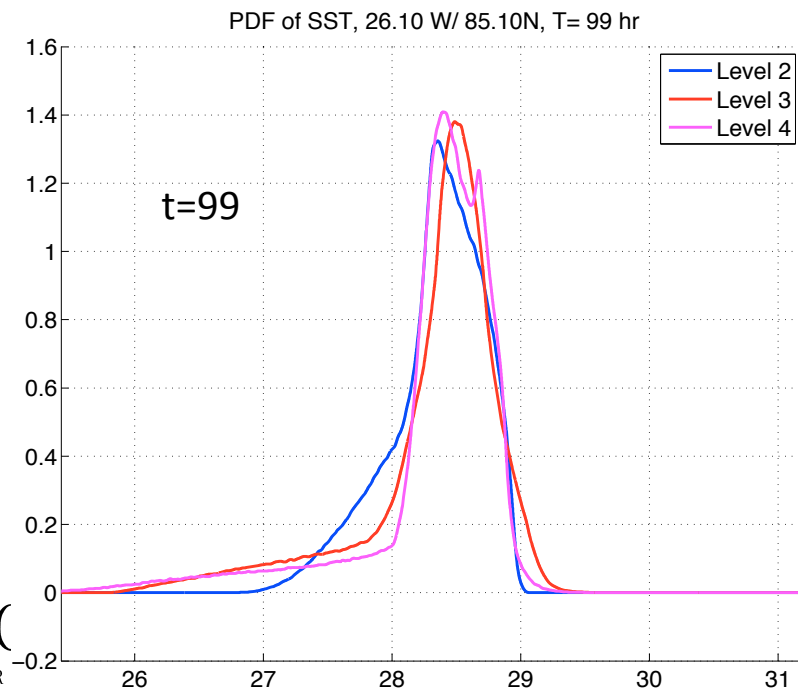
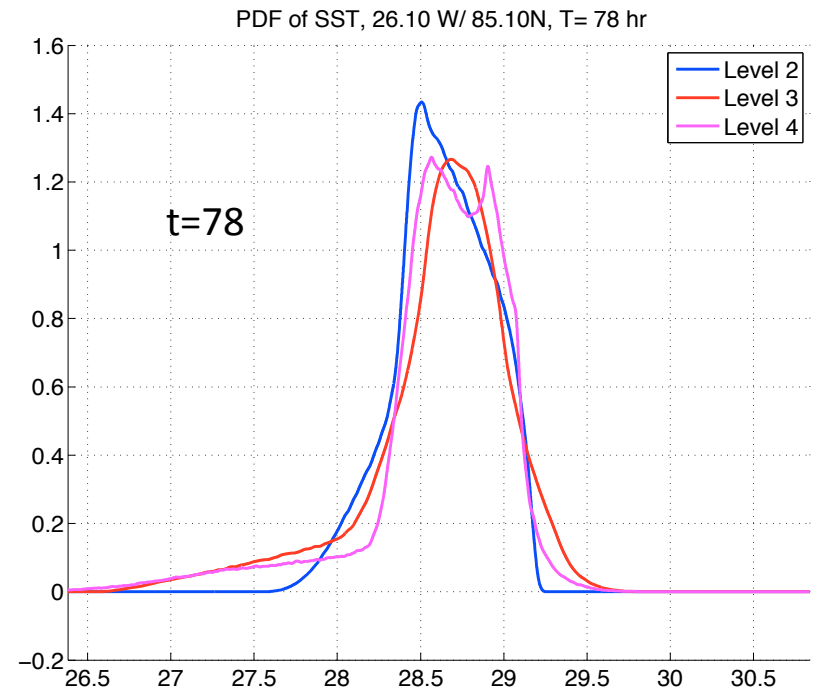
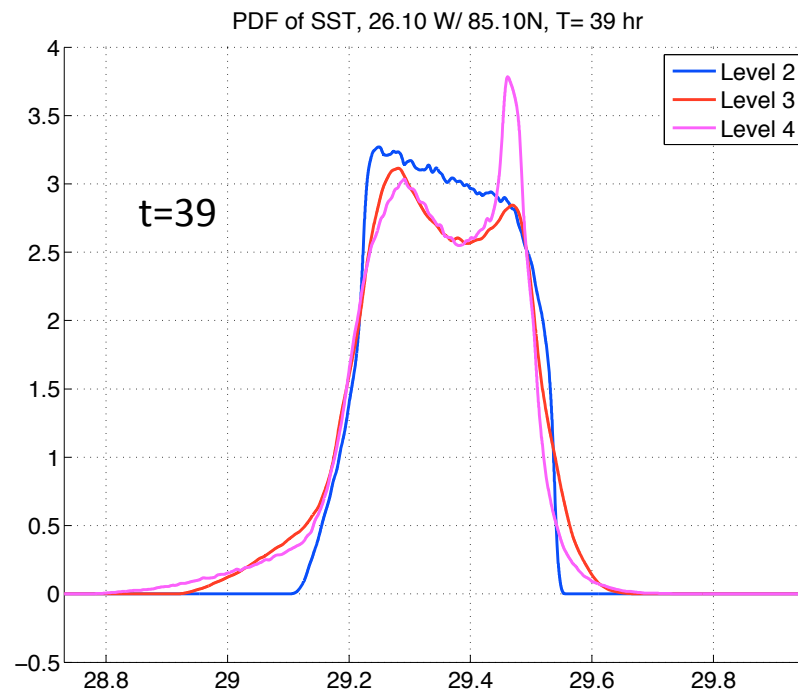
ξ_4



ξ_{1-3}



PDFs at different levels and order (p=l)



Bayesian Inference

Let H be a set of hypotheses made to model a set of data $\mathbf{D}$. Bayes theorem states:

$$p(H|\mathbf{D}) \propto p(\mathbf{D}|H) p(H)$$

where $p(H | \mathbf{D})$ is the posterior probability, $p(\mathbf{D} | H)$ is the likelihood function and $p(H)$ is the prior of H .

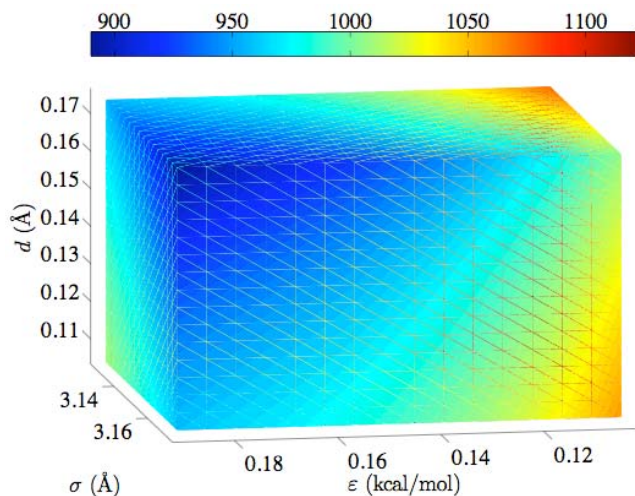
In our case H is the set of coefficients we want to infer:

- Model parameters
- PC coefficients themselves. This may be essential when model realizations are noisy!

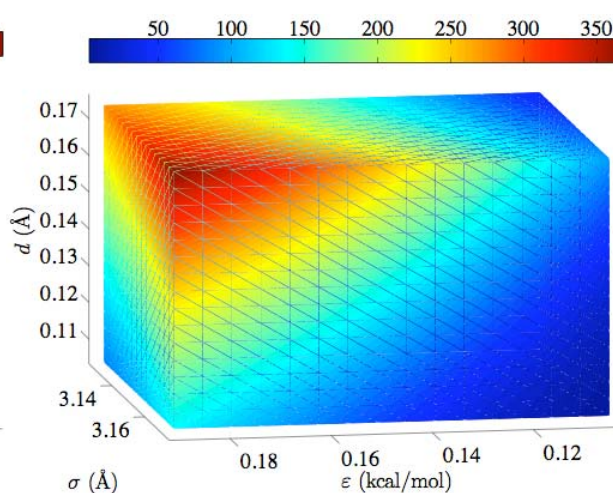
When PC representation of stochastic system is available, inference exercise can be greatly accelerated because it is **MUCH CHEAPER** to sample the PC representation than the forward model itself.

3D Example

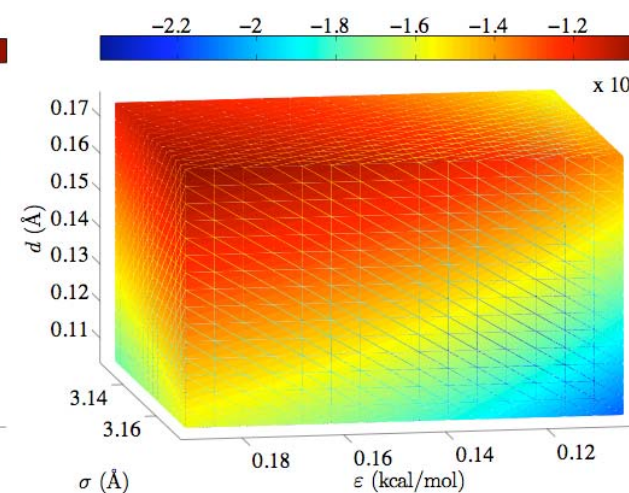
- **True** model: Synthetic molecular dynamics simulations of water.
- **Three hidden parameters:** $\epsilon_t = 0.17$; $\sigma_t = 3.15$, $d_t = 0.14$
- Goal: model inference based on 5 **noisy** realizations
- **Surrogate** model for **density**, **mean-square displacement** (self-diffusion) and **enthalpy**:
 - 3rd-order expansion, obtained based on 7-point Gauss quadrature with multiple realizations at each quadrature point
 - Illustration based on MAP estimate of PC coefficients



density



MSD



enthalpy

Inference based on 1 and 3 observables

