

Modeling of IC Variability

**Simulation and Characterization of Statistical CMOS Variability
and Reliability**

SISPAD 2010 Workshop

September 9th, 2010, Bologna, Italy

Kedar Patel, SanDisk/UC Berkeley

Costas J. Spanos, UC Berkeley



UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

Introduction

- IC variability originates from interacting layout components, manufacturing imperfections, and randomness at the atomistic scale.
- IC variability has a hierarchical & hybrid character
 - Its hierarchy reflects the nature of production (*device, chip, field, wafer, and wafer-lot*)
 - It is *hybrid*, because at each levels variability consists of *systematic (deterministic)* and *random* components.
- A complete, yet *parsimonious* statistical model is needed to capture and describe variability.



Outline

- Introduction
- Modeling and Case Studies
 - Random Variability
 - Systematic (Deterministic) Variability
 - Global Hierarchical Variability Model
- Future

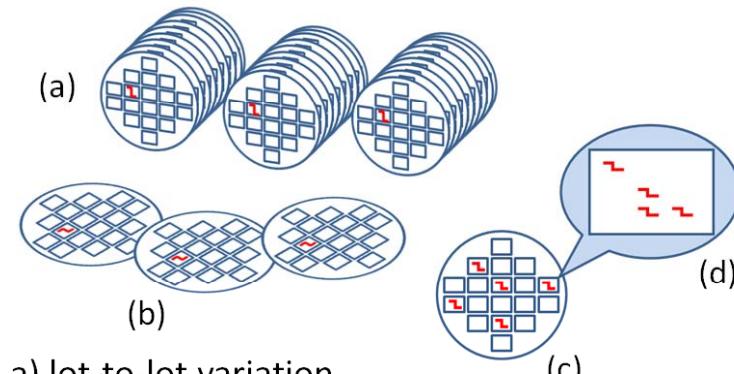


UNIVERSITY OF CALIFORNIA • BERKELEY

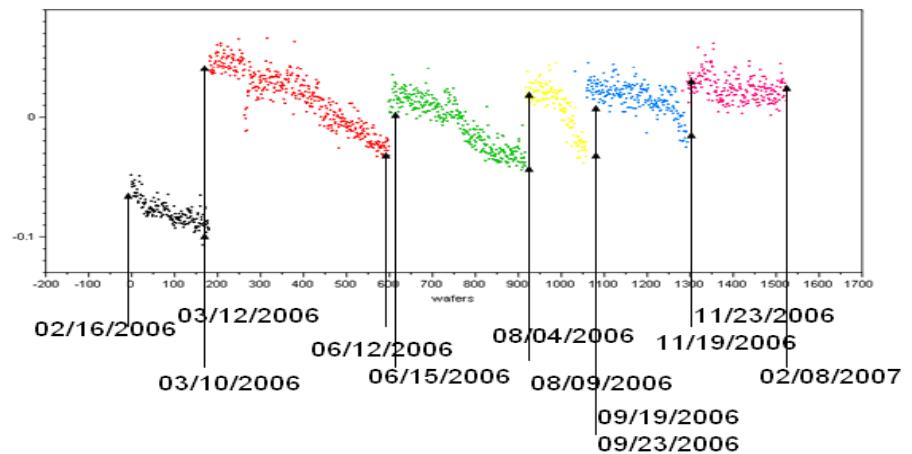
SanDisk®

Why is it such a hard problem?

- Dual Nature: Random vs. Systematic
- Various levels of *Hierarchy*
 - die, field, wafer, lot
- Various *consumers* of variability information
 - device, process, circuit engineers
- A large portion of variability is not stationary



a) lot-to-lot variation
b) wafer-to-wafer variation
c) die-to-die or across-wafer variation
d) within-die variation



Model Hierarchy (lot, wafer, within wafer, within die)

$$p_{ijkl} = \eta + \lambda_i + \sigma_j + \alpha_{ij} + \beta_k + \omega_{ijk} + \gamma_l + \tau_{kl} + \epsilon_{ijkl}$$

Model Estimator	Description
$\hat{\eta} = \bar{p}_{....}$	Global Mean
$\hat{\lambda}_i = \bar{p}_{i...} - \bar{p}_{....}$	Lot Factor
$\hat{\sigma}_j = \bar{p}_{.j..} - \bar{p}_{....}$	Wafer or Slot Factor
$\hat{\alpha}_{ij} = \bar{p}_{ij..} - \bar{p}_{i...} - \bar{p}_{.j..} + \bar{p}_{....}$	Lot-Wafer Interaction Factor
$\hat{\beta}_k = \bar{p}_{..k.} - \bar{p}_{....}$	Average Wafer
$\hat{\omega}_{ijk} = \bar{p}_{ijk.} - \bar{p}_{ij..} - \bar{p}_{..k.} + \bar{p}_{....}$	Deviation from Average Wafer
$\hat{\gamma}_l = \bar{p}_{...l} - \bar{p}_{....}$	Average Die
$\hat{\tau}_{kl} = \bar{p}_{..kl} - \bar{p}_{..k.} - \bar{p}_{...l} + \bar{p}_{....}$	Die-Site Interaction
$\hat{\epsilon}_{ijkl} = p_{ijkl} - \bar{p}_{ijk.} + \bar{p}_{..k.} - \bar{p}_{..kl}$	Residual



Outline

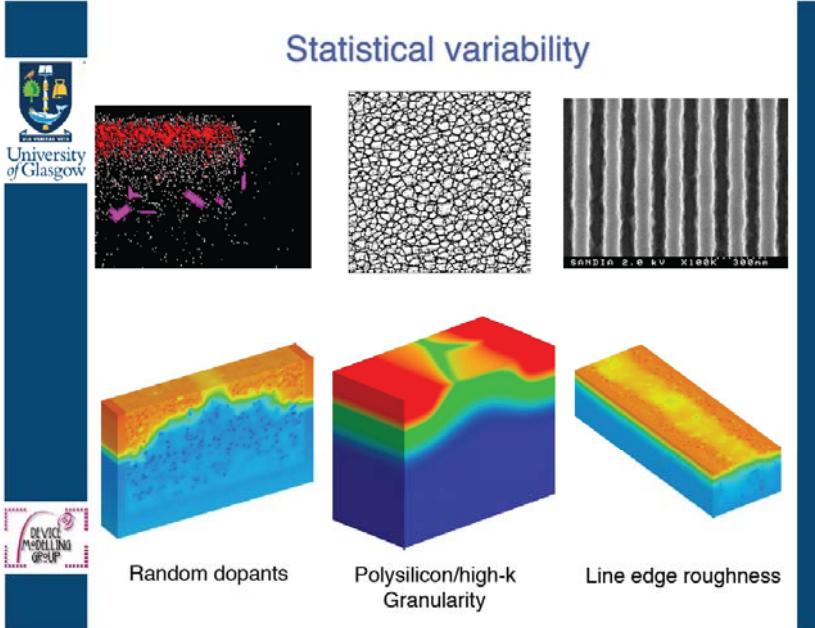
- Introduction
- Modeling and Case Studies
 - Random Variability
 - Systematic (Deterministic) Variability
 - Global Hierarchical Variability Model
- Future



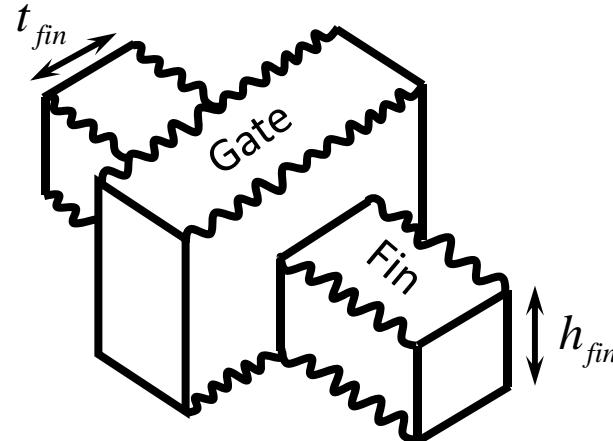
UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

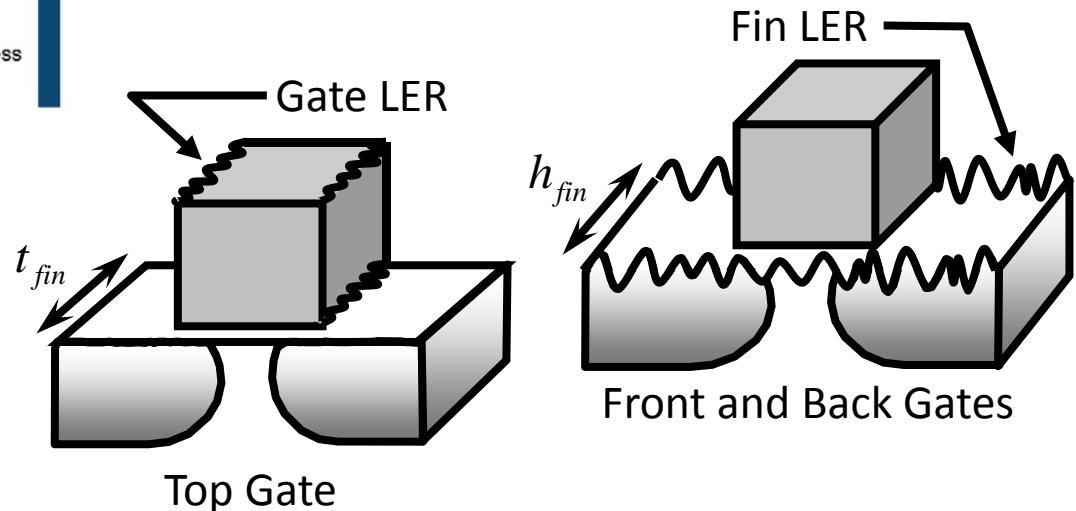
Intrinsic (Random) Variability



IEEE/ACM Workshop on Variability Modeling and Characterization
ICCAD 2009
Scott Roy (Univ. of Glasgow): Atomistic Simulation of Variability

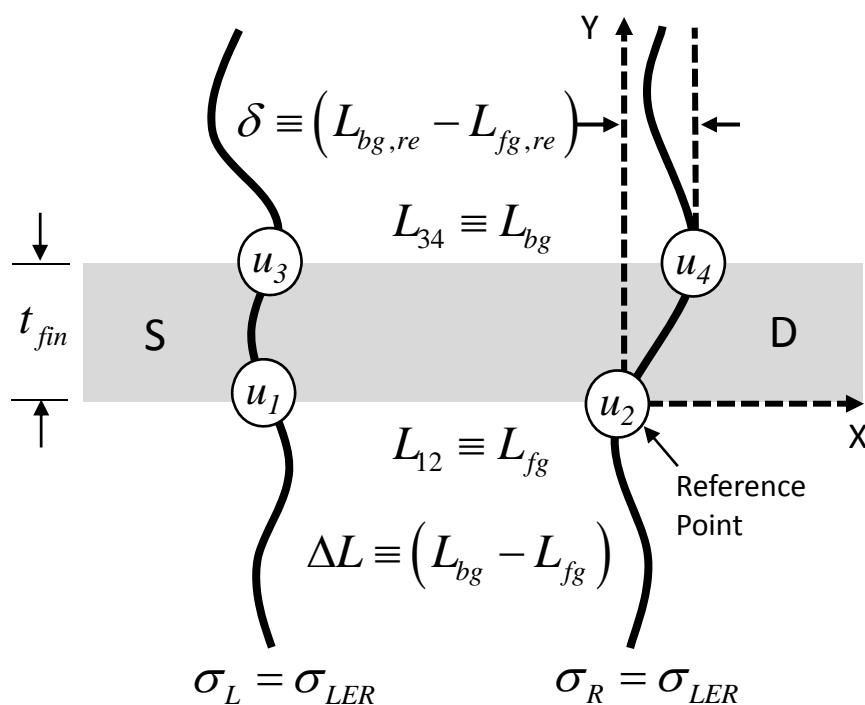
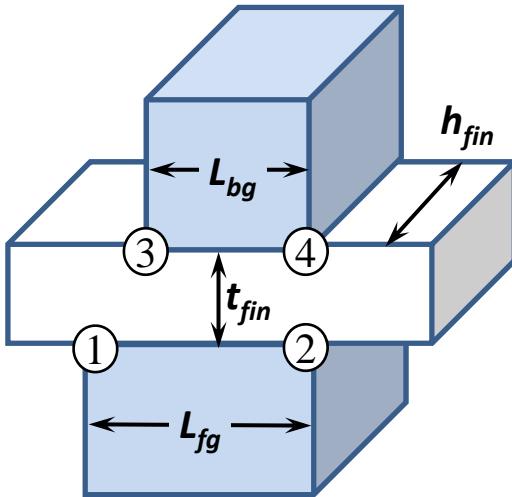


(Patel, Spanos and King-Liu, TED 2009)



UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®



LER Model Description

(Patel, Spanos and King-Liu, TED 2009)

$$\sigma_\delta^2 = 2\sigma_{LER}^2 \left(1 - \rho_A(t_{fin})\right)$$

$$\rho(y) = e^{-\left(\frac{|y|}{\xi}\right)^{2\alpha}}$$

Auto-correlation function

For a resist-defined gate electrode,

$$\sigma_{\Delta L}^2 = 4\sigma_{LER}^2 \left[1 - \rho_A(t_{fin})\right].$$

For a spacer-defined gate electrode ,

$$\sigma_{\Delta L}^2 = 0$$



UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

LER Simulation Details

TABLE 1: 2-D DEVICE SIMULATION PARAMETERS

Electrical/Doping	Structural
$V_{dd}=0.9V$	$L_g=13nm$
$\phi_m=4.62eV$	$t_{ox}=6A$
$N_B=1e15 cm^{-3}$	$L_{sp}=7.2nm$
$N_{s/d}=1e20 cm^{-3}$	$t_{fin}=7.5nm$
$\sigma_{s/d}=4nm/dec$	$t_{poly}=13nm$

TABLE 2: 2-D NOMINAL DEVICE PERFORMANCE PARAMETERS.

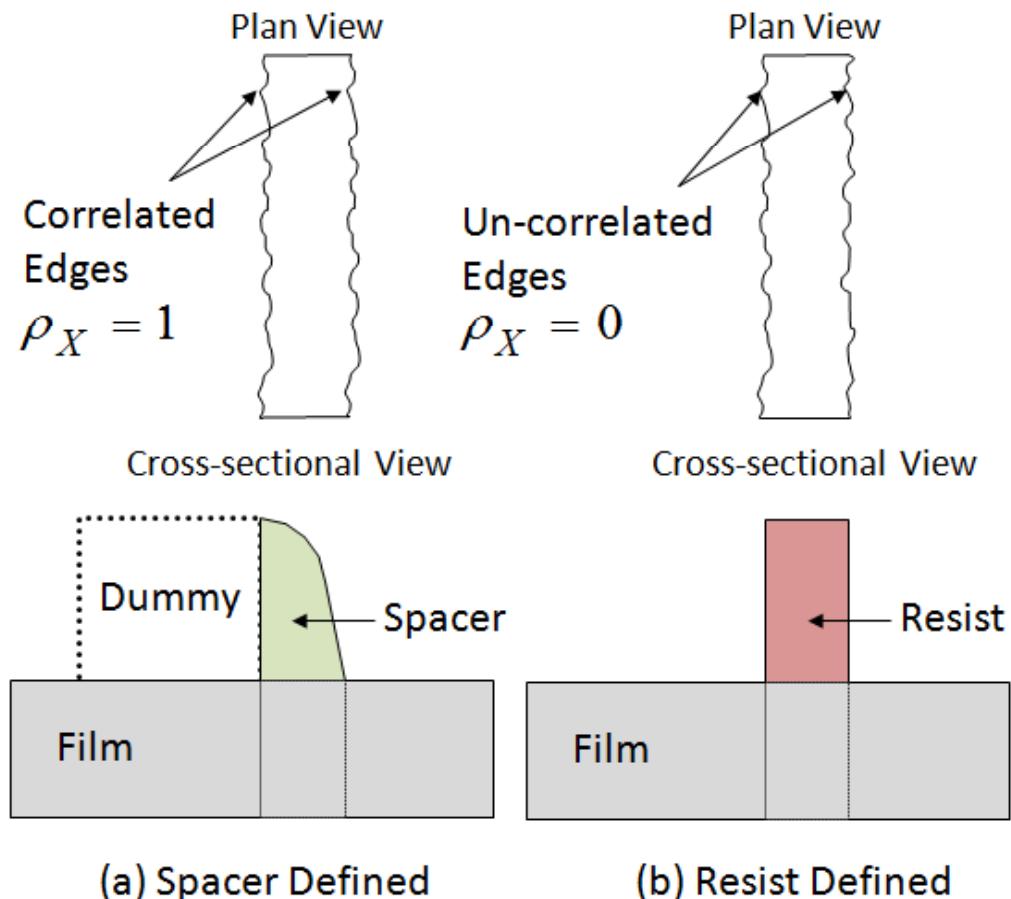
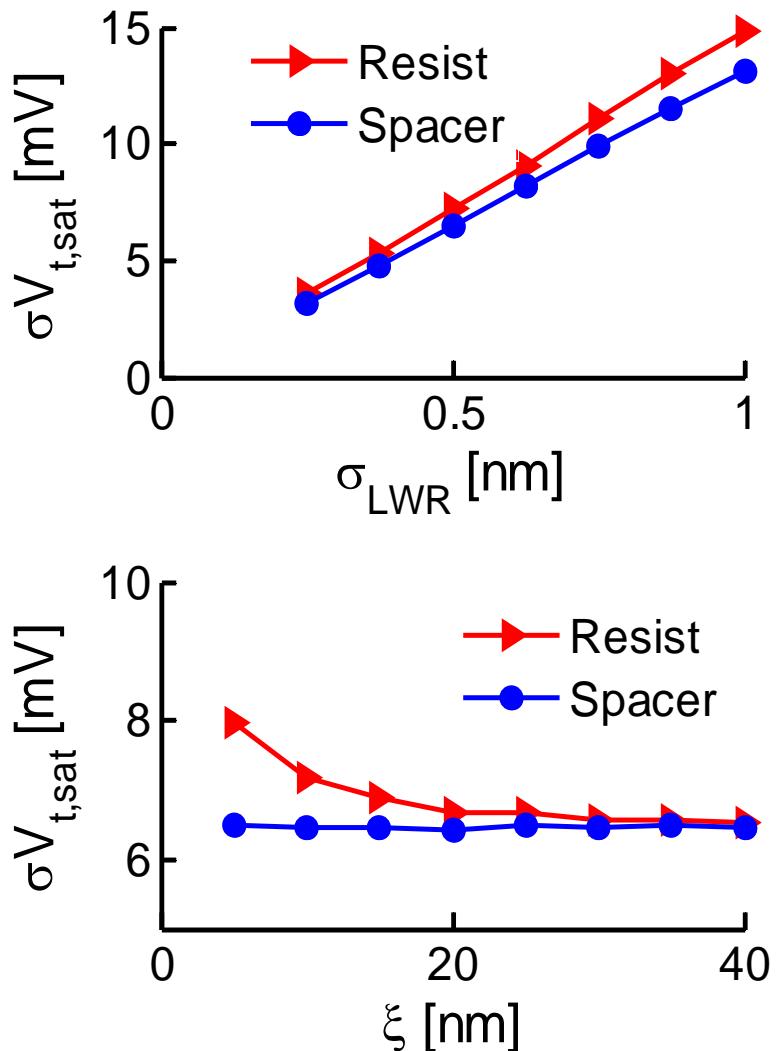
Parameter	Units	Value
$V_{t,sat}$	mV	210
SS	mV/dec	69
DIBL	mV/V	30
$g_{m,sat}$	mA/V	6.75
$I_{d,sat}$	mA/ μm	2.48
I_{off}	pA/ μm	94.4



UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

Spacer v. Resist



$$\sigma_{LWR}^2 = 2\sigma_{LER}^2 (1 - \rho_X) \quad \sigma_L = \sigma_R \equiv \sigma_{LER}$$



UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

Outline

- Introduction
- Modeling and Case Studies
 - Random Variability
 - Systematic (Deterministic) Variability
 - Global Hierarchical Variability Model
- Future

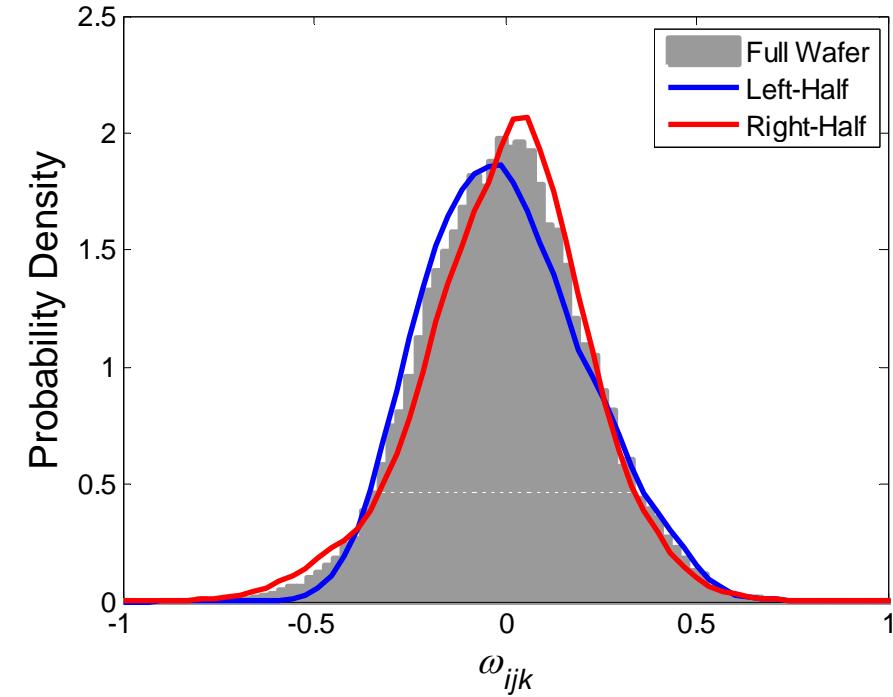
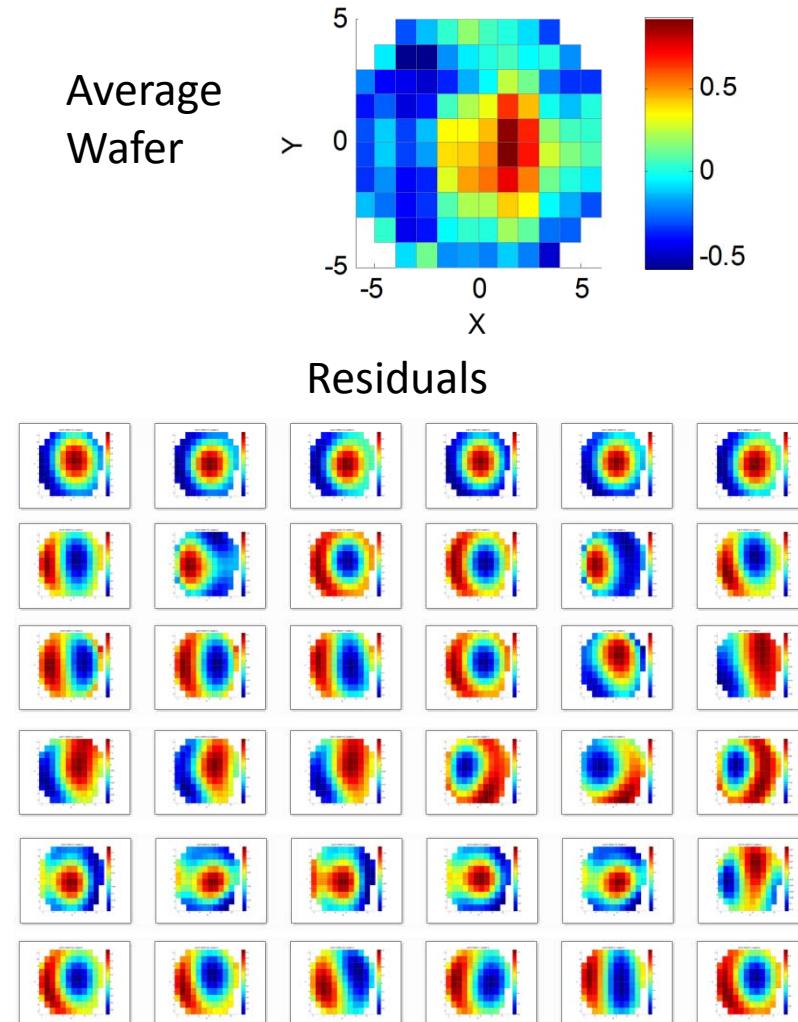


UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

The Statistics of Spatial Variability

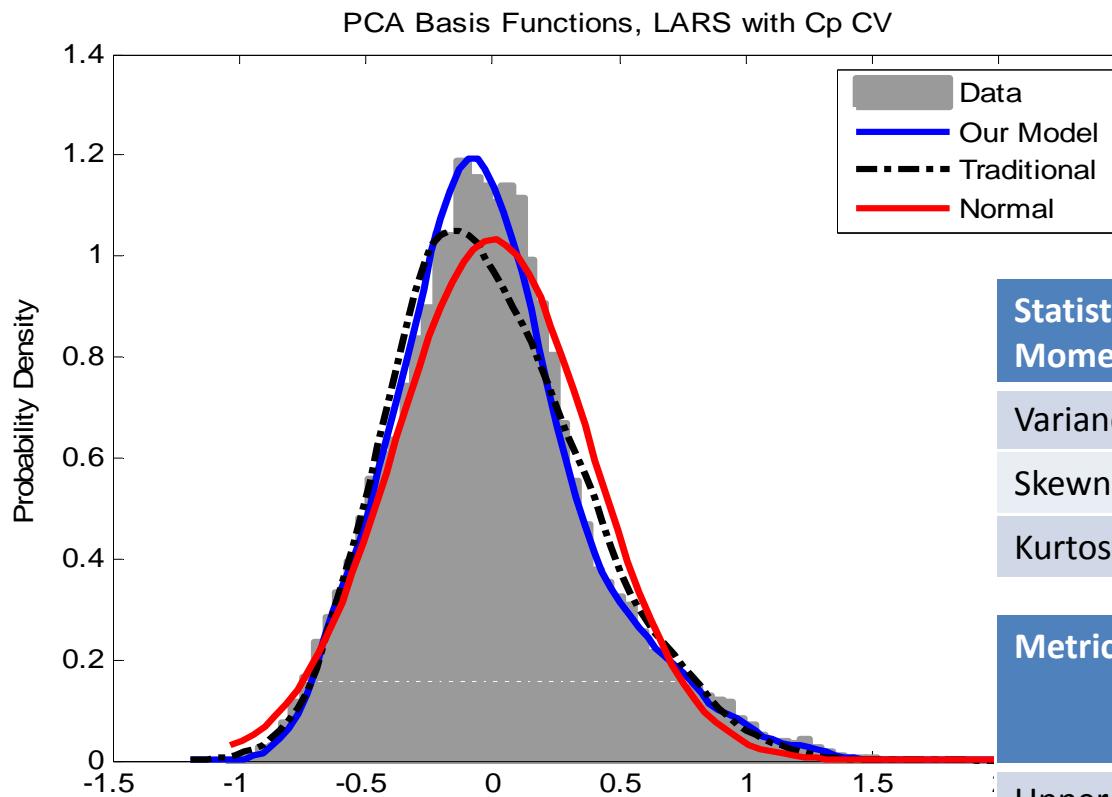
Ring Oscillator Frequency, 65nm node



UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

Results using PCA Basis Functions



Traditional Method:
 $\hat{\beta} + \varepsilon_{\hat{\omega}}$
 $\varepsilon_{\hat{\omega}} \sim N(0, \text{var}(\hat{\omega}_{ijk}))$

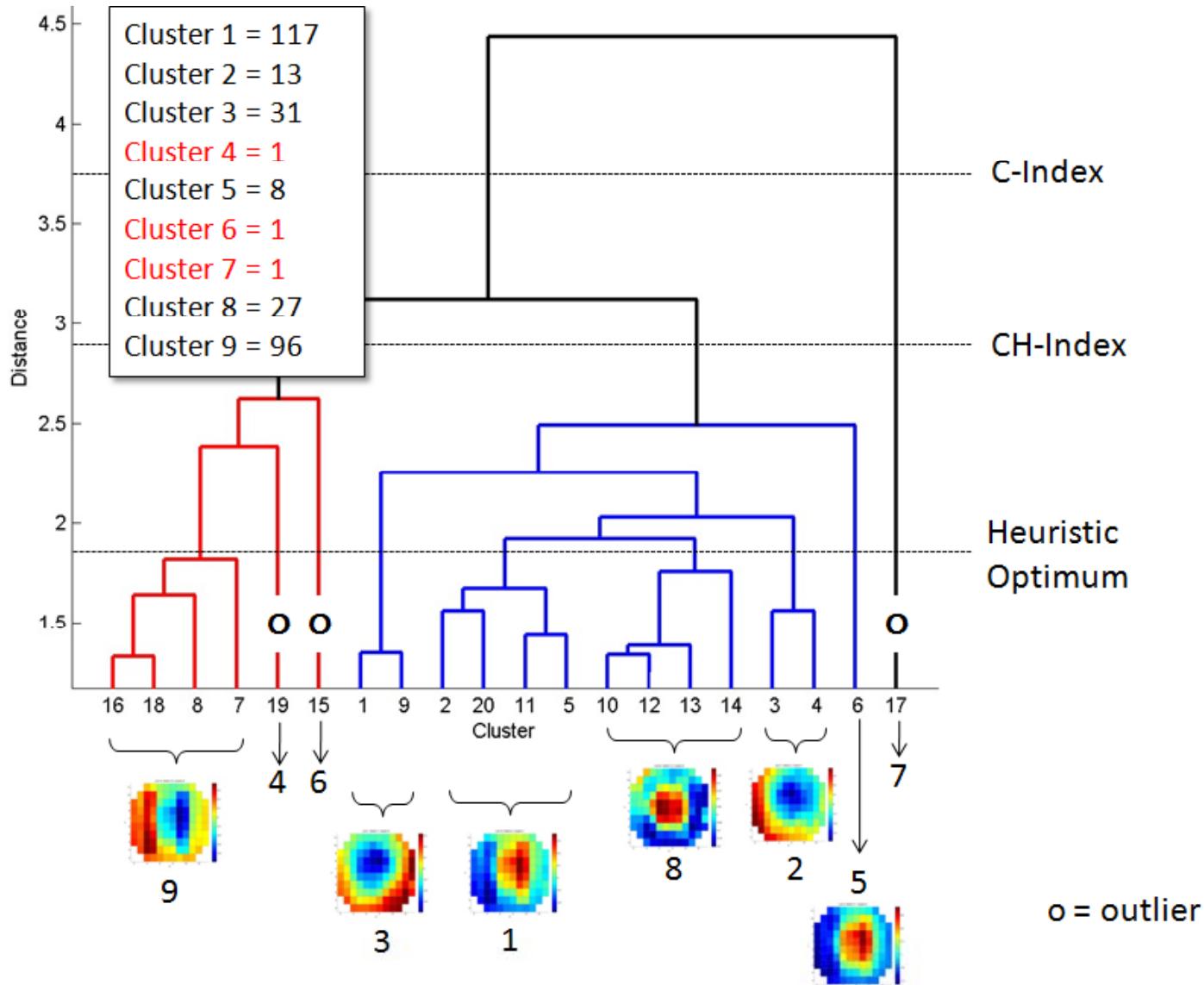
Proposed Method:
 $\hat{\beta} + \tilde{\omega} + \varepsilon_R$
 $\varepsilon_R \sim N(0, \sigma_R^2)$
 $R = \hat{\omega}_{ijk} - \tilde{\omega}$

Statistical Moment	Data	Traditional Model	Our Model
Variance	0.149	0.147	0.142
Skewness	0.545	0.401	0.563
Kurtosis	3.555	3.002	3.544

Metric	% Actual Data [95% CI]	% Traditional Model	% Our Model
Upper Tail	1.47 [1.34, 1.61]	1.00	1.45
Lower Tail	0.02 [0.00, 0.03]	0.09	0.02
Out of Spec [-1, 1]	1.49 [1.35, 1.62]	1.00	1.45



A Bonus Application: Cluster Analysis



UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

Outline

- Introduction
- Modeling and Case Studies
 - Random Variability
 - Systematic (Deterministic) Variability
 - Global Hierarchical Variability Model
- Future

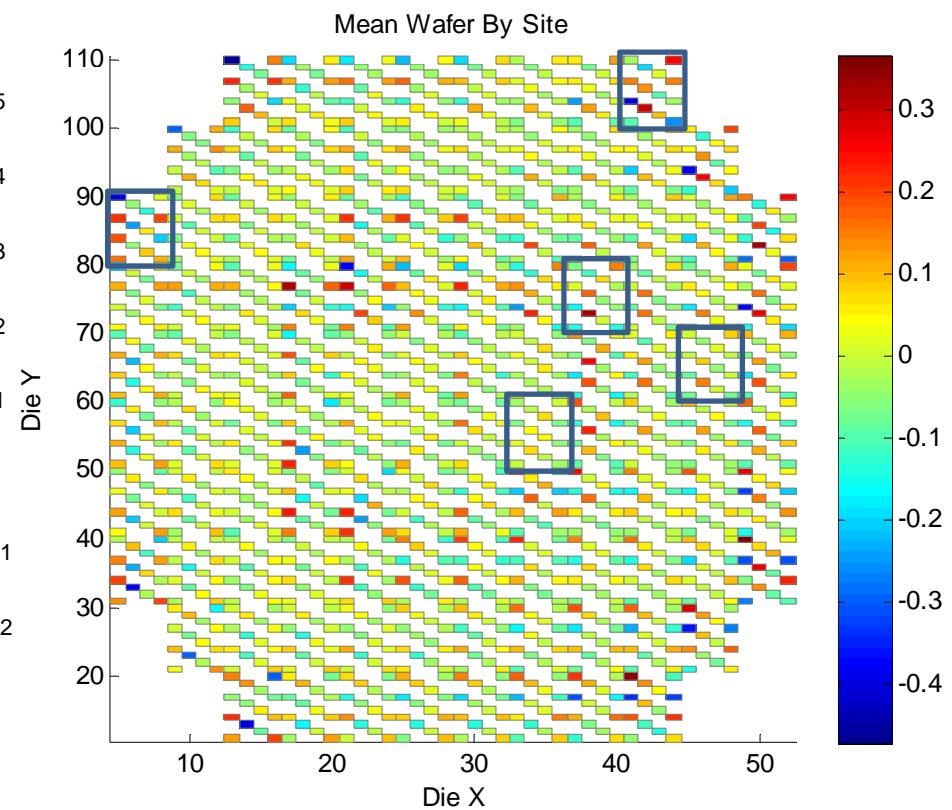
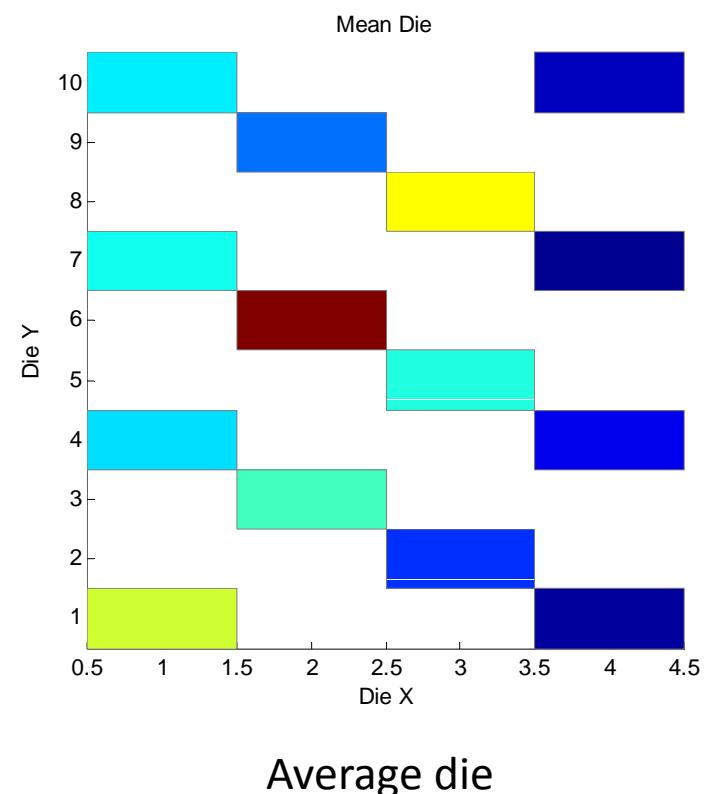


UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

Within-die Variation

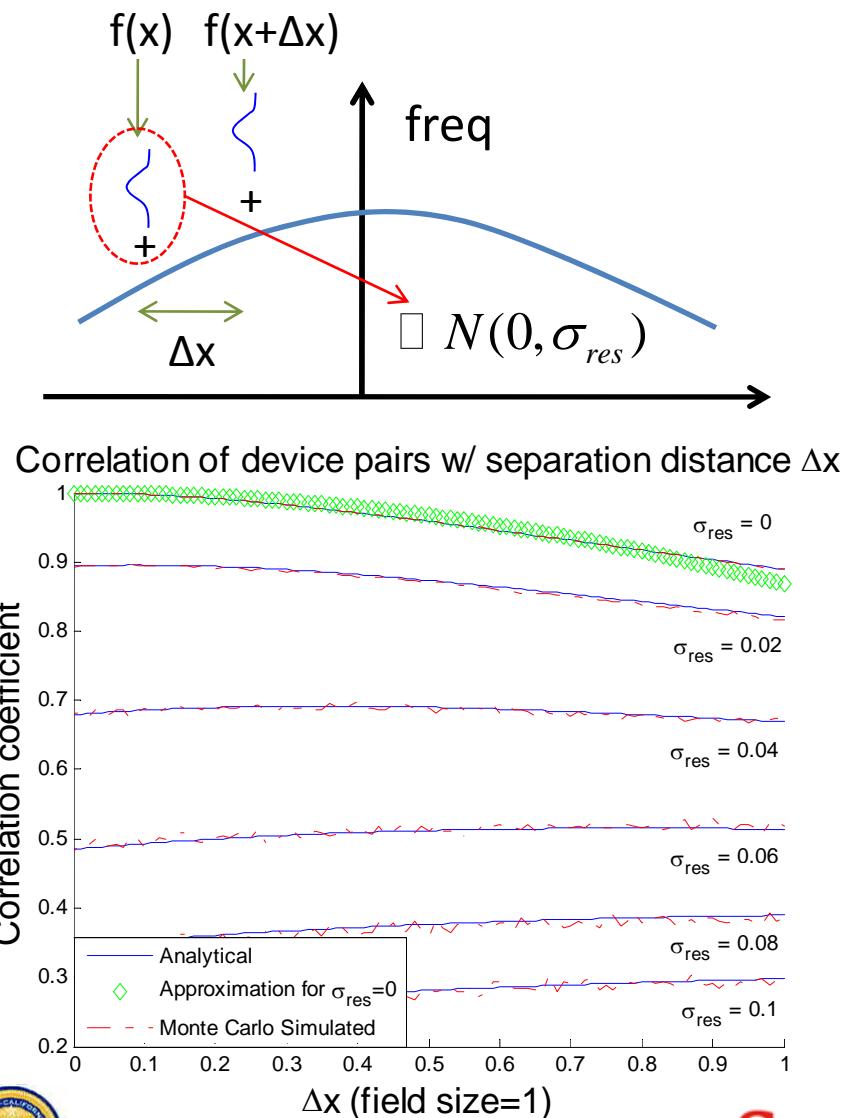
$$p_{ijkl} = \eta + \lambda_i + \sigma_j + \rho_{ij} + \beta_k + \omega_{ijk} + \gamma_l + \tau_{kl} + \delta_{ijkl}$$



UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk Die-level residuals

Apparent Spatial Correlation



$$Z_1 = f(x, y) + e_1$$

$$Z_2 = f(x + \Delta x, y) + e_2$$

$$\approx f(x, y) + \frac{\partial f(x, y)}{\partial x} \Delta x + e_2$$

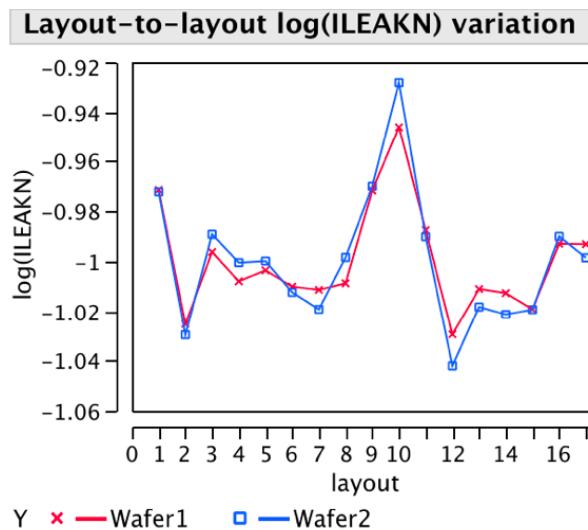
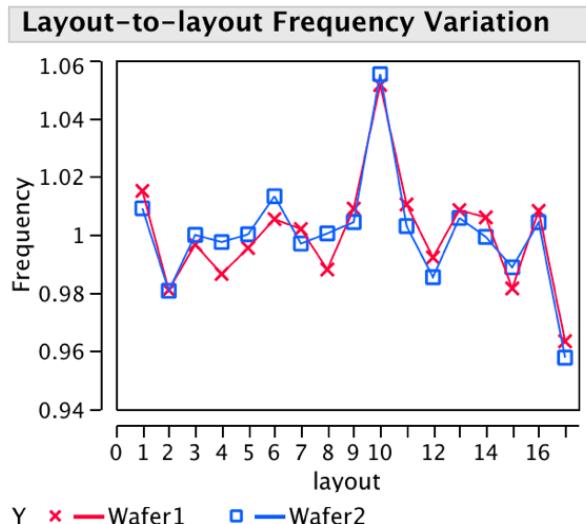
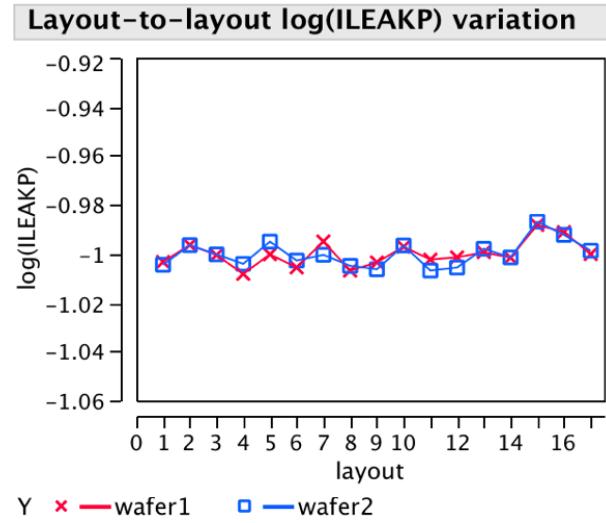
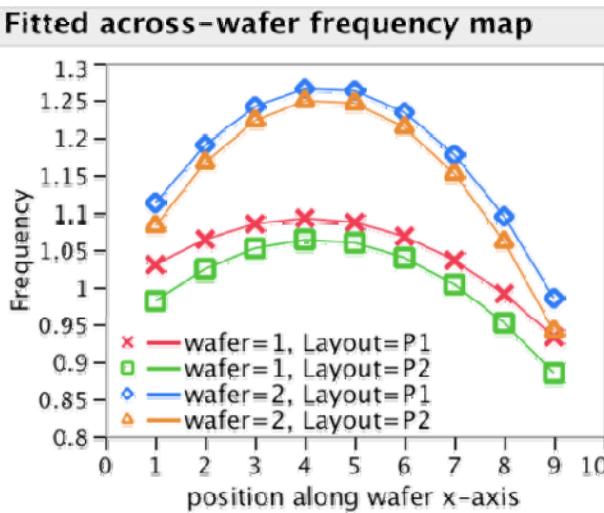
>> Unmodeled Systematic Variation Exhibits Spatial Correlation



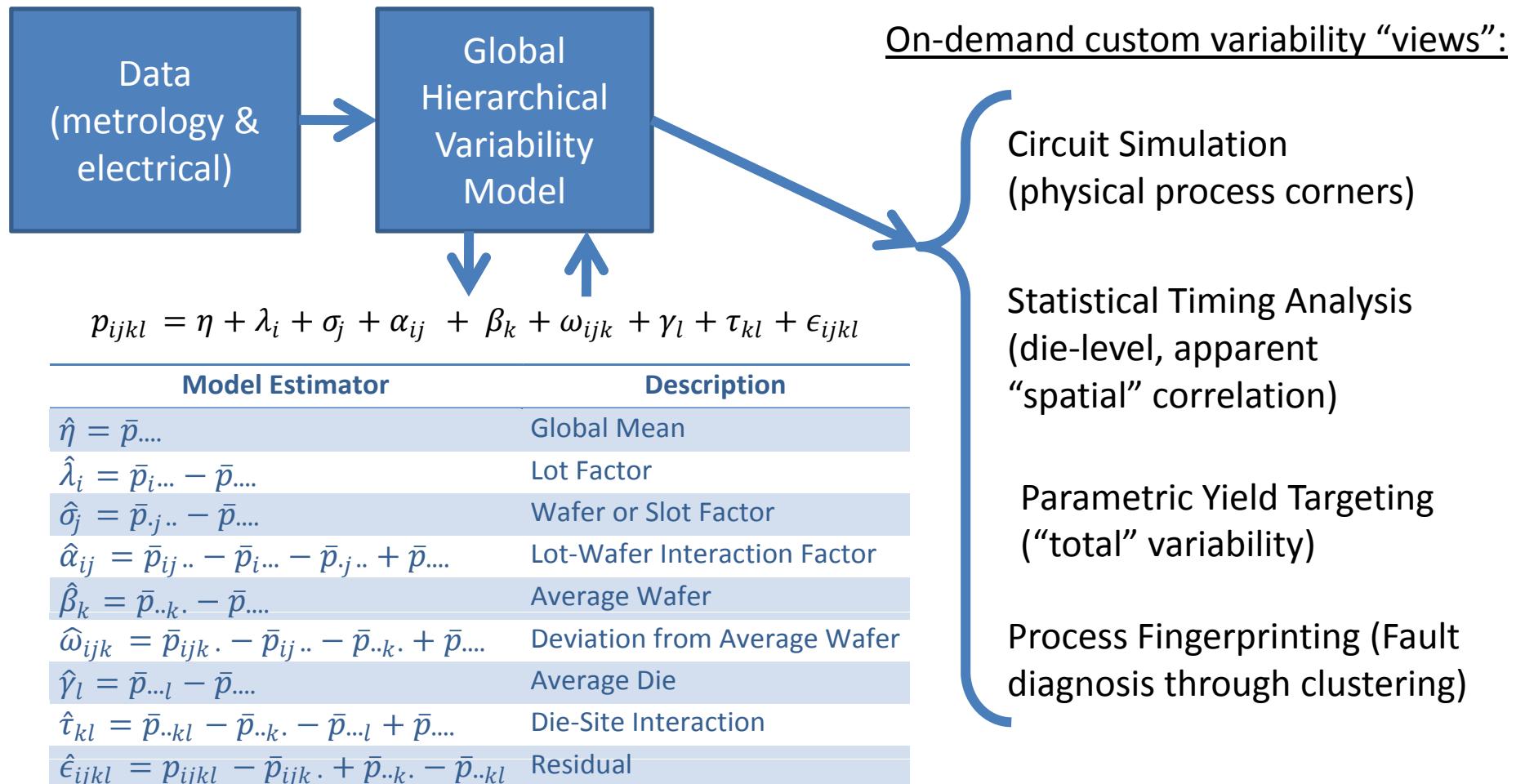
UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

Layout Effect Analysis



Global Hierarchical Variability Model



Outline

- Introduction
- Modeling and Case Studies
 - Random Variability
 - Systematic (Deterministic) Variability
 - Global Hierarchical Variability Model
- Future



UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

Of Further Interest

- What about Statistical Circuit Simulation?
 - Propagating Gaussian and Mixture of Gaussian (MOG) distributions through interval representation
- What about temporal non-stationarity?
 - Can be modeled or “collapsed” depending on the needed “view”
- What about SRAM variability?
 - Nothing special other than we really must capture extreme tails of distribution extremely well (see above)



UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

Acknowledgements

- Graduate Students at UC Berkeley: Yu Ben, Jason Cain, Paul Friedberg, Justin Ghan, Kun Qian, Ying Qiao, Anand Subramanian, QianYing Tang, Dekong Zeng
- In collaboration with Professors Puneet Gupta (UCLA), Bora Nikolic, Tsu-Jae King, Kameshwar Poolla (UCB), and Dr. Sani Nassif (IBM)
- Datasets from IBM (Dr. Sani Nassif) and BWRC/ST (through Professor Bora Nikolic)
- Funding from SRC, IMPACT/UC Discovery, C2S2 and TSMC



UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

Thank you for your attention!

Questions?

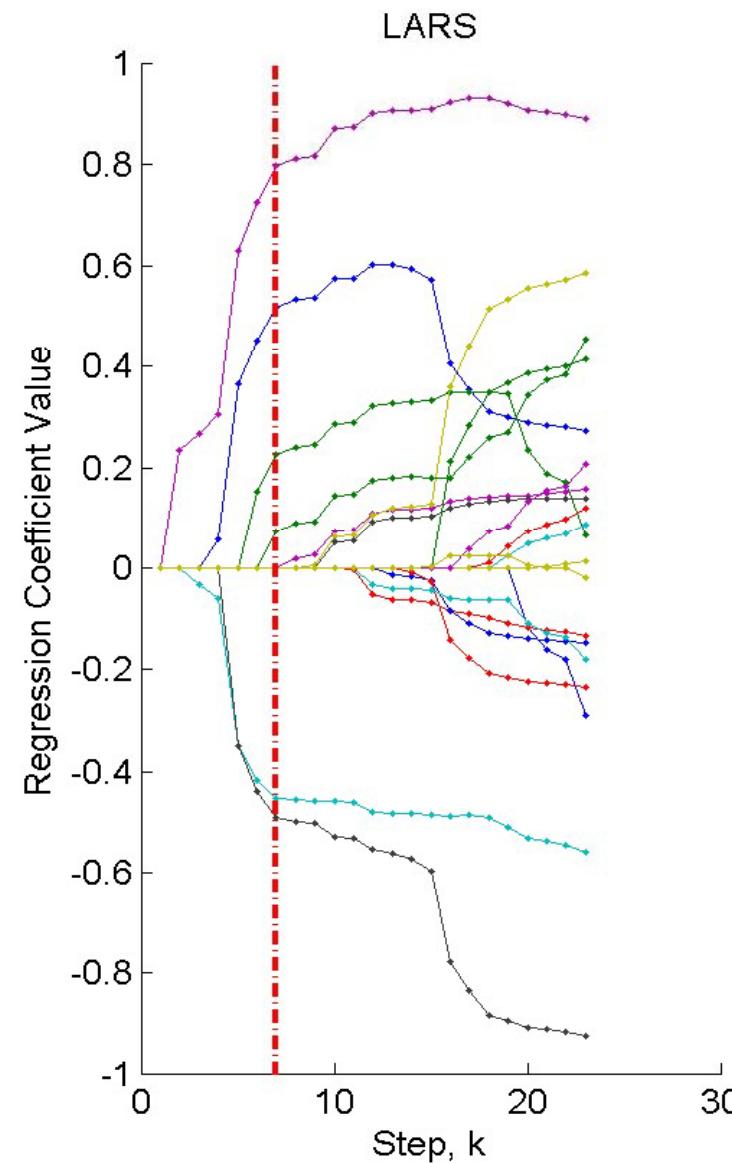
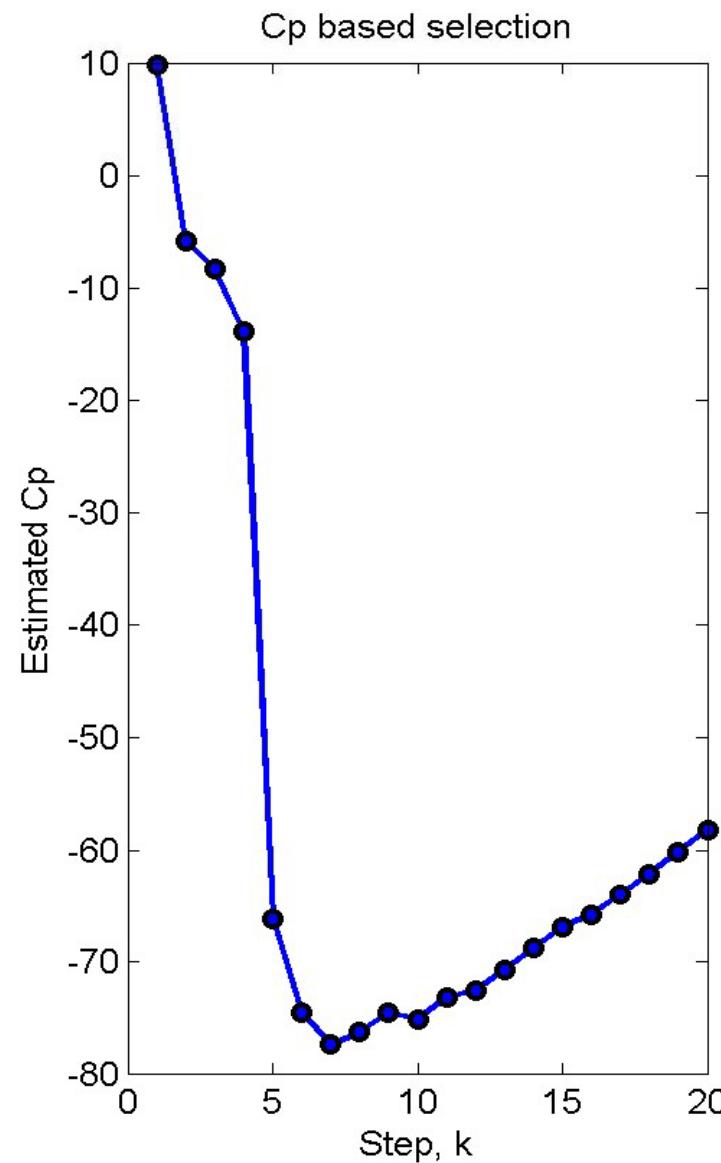


UNIVERSITY OF CALIFORNIA • BERKELEY

SanDisk®

23

Least Angle Regression with Cp Selection



Lot 7, Wafer 9, Terms = 1, 2, 4, 7, 9, 12

