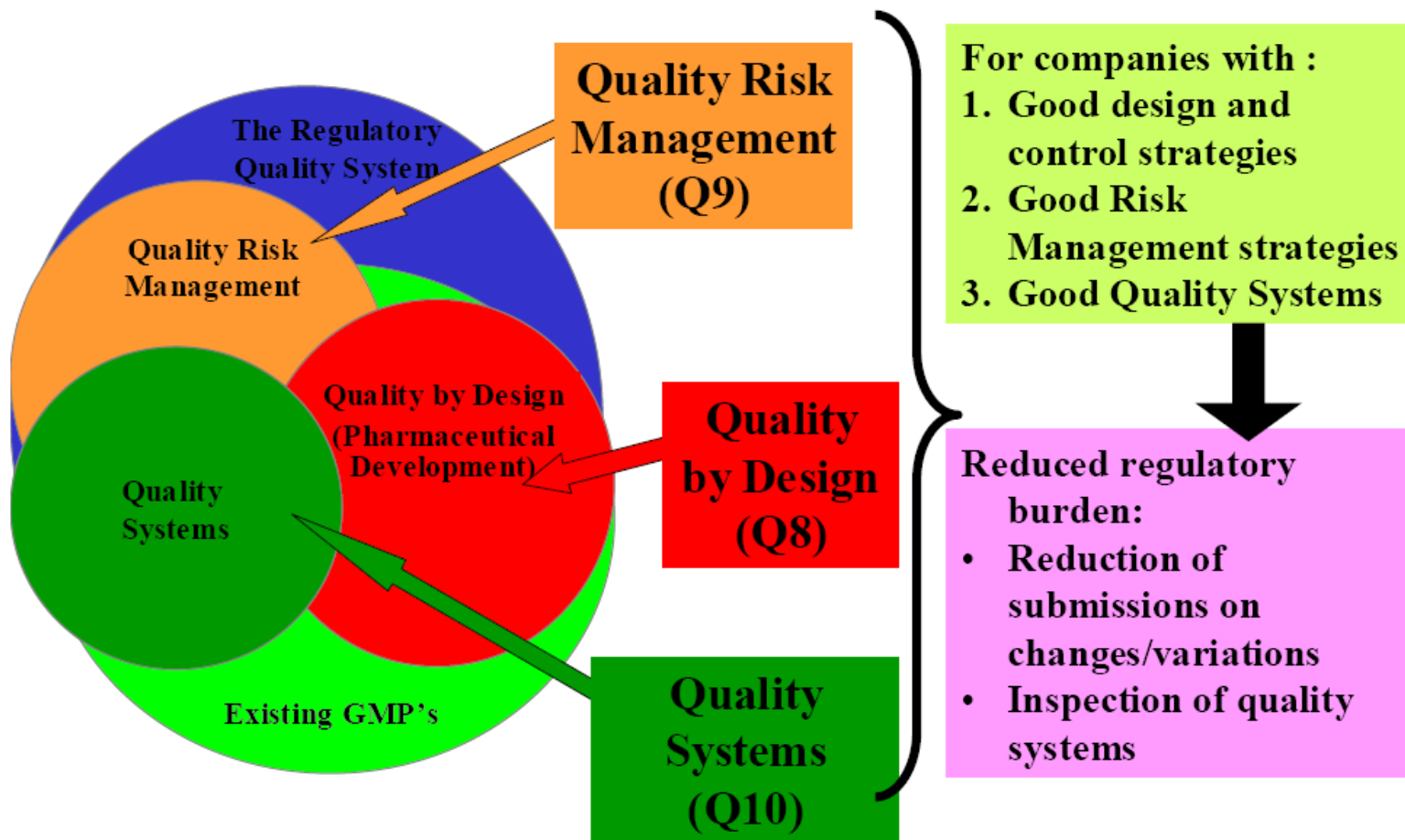

Bayesian Approach to Specification of Design Space

Paul van Eikeren and Corey Dow-Hygelund
userR! 2009 (July 8-10, 2009)

Quality by Design: Pharmaceutical Quality Vision

Pharmaceutical Quality Vision

Develop a harmonized pharmaceutical quality system applicable across the lifecycle of the product emphasizing an integrated approach to quality risk management and science.



Guidance for Industry

Q8(R1) Pharmaceutical Development

U.S. Department of Health and Human Services
Food and Drug Administration
Center for Drug Evaluation and Research (CDER)
Center for Biologics Evaluation and Research (CBER)

June 2009
ICH

Revision 1

- QbD Pharmaceutical Development
 - Quality Target Product-Profile
 - Critical Quality Attributes (CQA)
 - Risk Assessment: link to Product CQA
 - Design Space
- What is Design Space
 - “The multidimensional combination and interaction of input variables (e.g., material attributes) and process parameters **that have been demonstrated to provide assurance of quality.**”
 - “Working within the design space is not considered as a change.”
 - “Movement out of the design space is considered to be a change and would normally initiate a regulatory post-approval change process.”
 - “Design space is proposed by the applicant and is subject to regulatory assessment and approval.”

Quality by Design Workflow



Definition of **Product Intended Use** and pre-definition of **Quality targets** (wrt clinical relevance, efficacy and safety)

List of Unit Operations that lead to intended drug substance or drug product (could be analytical)

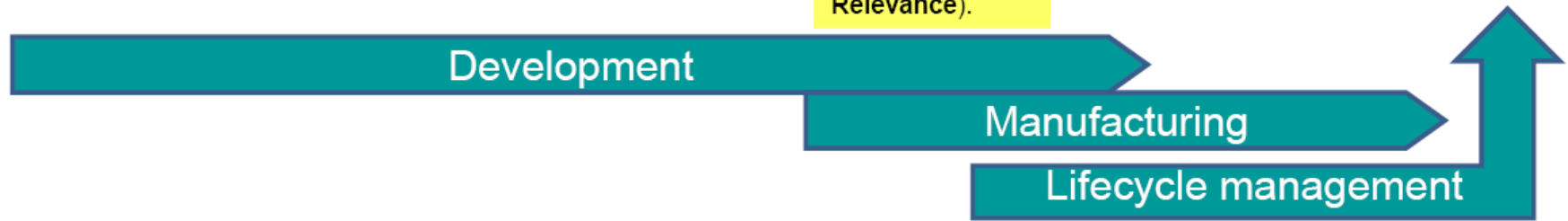
Summary of **Prior Scientific Knowledge** (drug substance, processes, Unit ops etc). **Initial Risk Assessment** to identify **Critical Quality Attributes**

Overview of **Quality by Design** key actions and decisions taken to develop **New Scientific Knowledge**, e.g. DoE, PAT, **Risk Assessment and Risk Control**

Summary of **Scientific Understanding of Material and Process**. Justification and description of **Multi-dimensional Space that Assures Quality** (interrelationships and boundaries of **Clinical Relevance**).

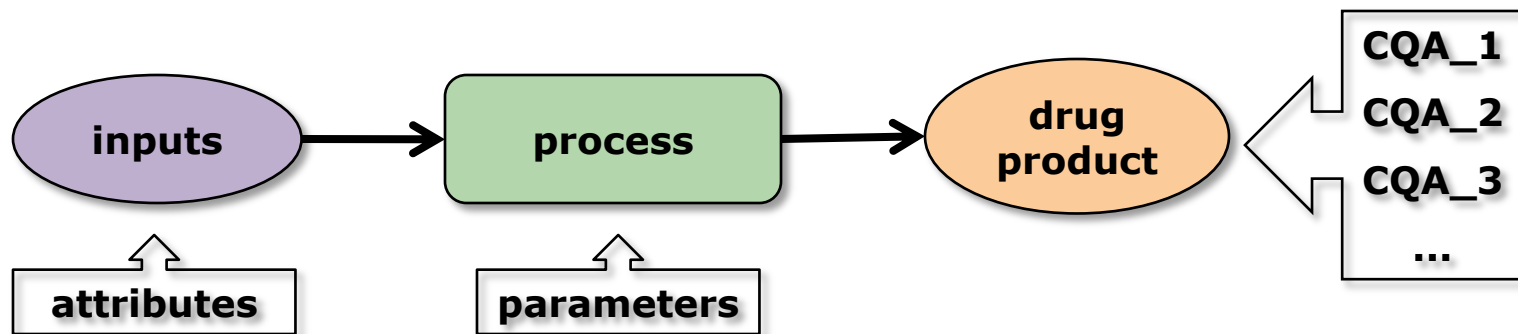
Definition of **Control Strategy** based on Design Space leading to **Control of Quality and Quality Risk Mgmt.** (Process Robustness)

Proposal for **Lifecycle Management** based on Product and Process Scientific Knowledge and **Quality Risk Mgmt.** (Materials, Site, Scale etc)

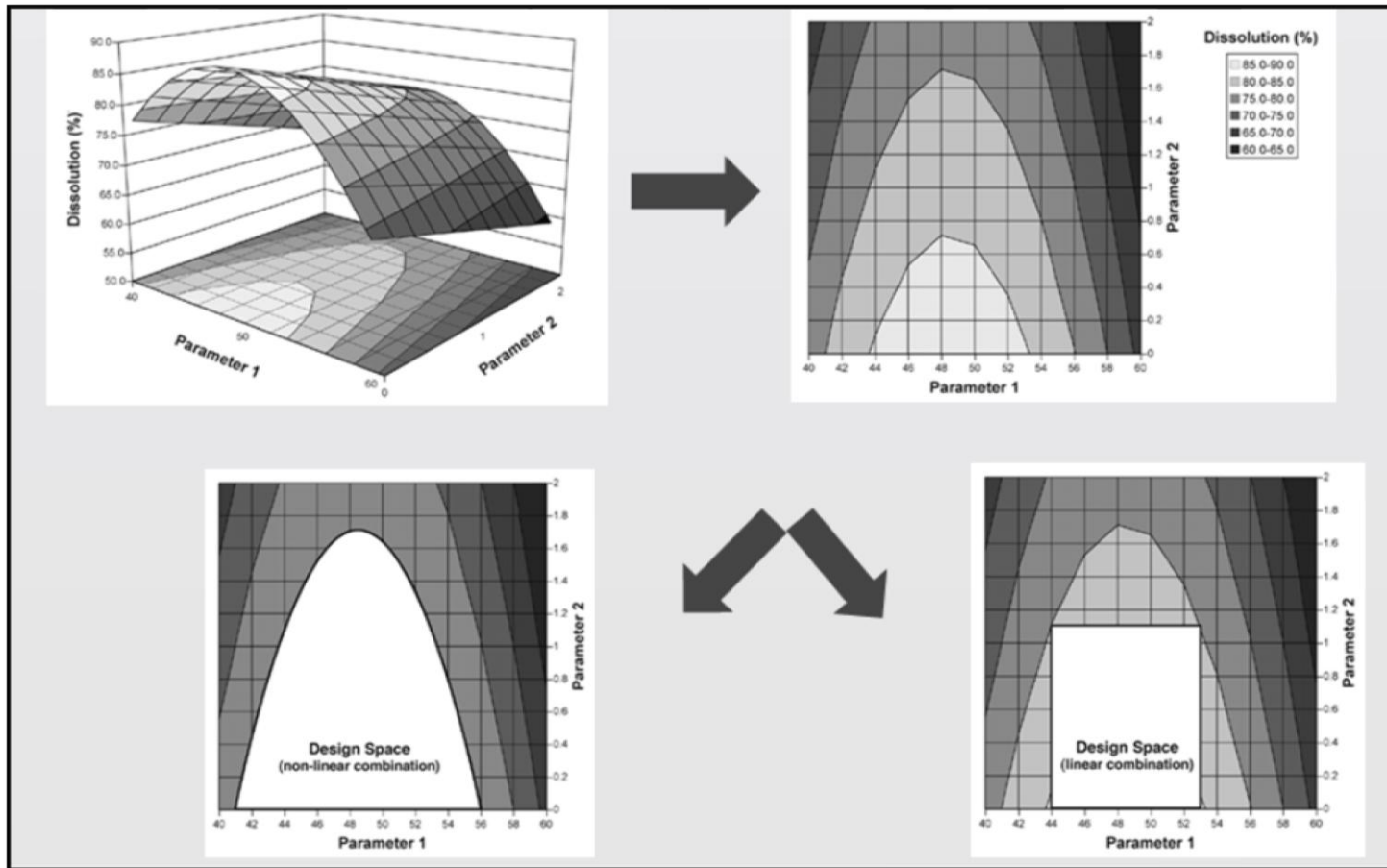


Elements of Design Space

- Risk based approach to assurance of quality
- Critical to quality attributes (CQA) are multivariate
- Quantitative model links input attributes and process parameters to CQAs
- Model quantifies risk of not meeting CQAs



Q8(R1) Example Design Space



Q1. How do we enable a risk-based approach to design space?

Q2. How do we best construct the design space?

Q3. How do we assess the reliability (assurance) of the design space?

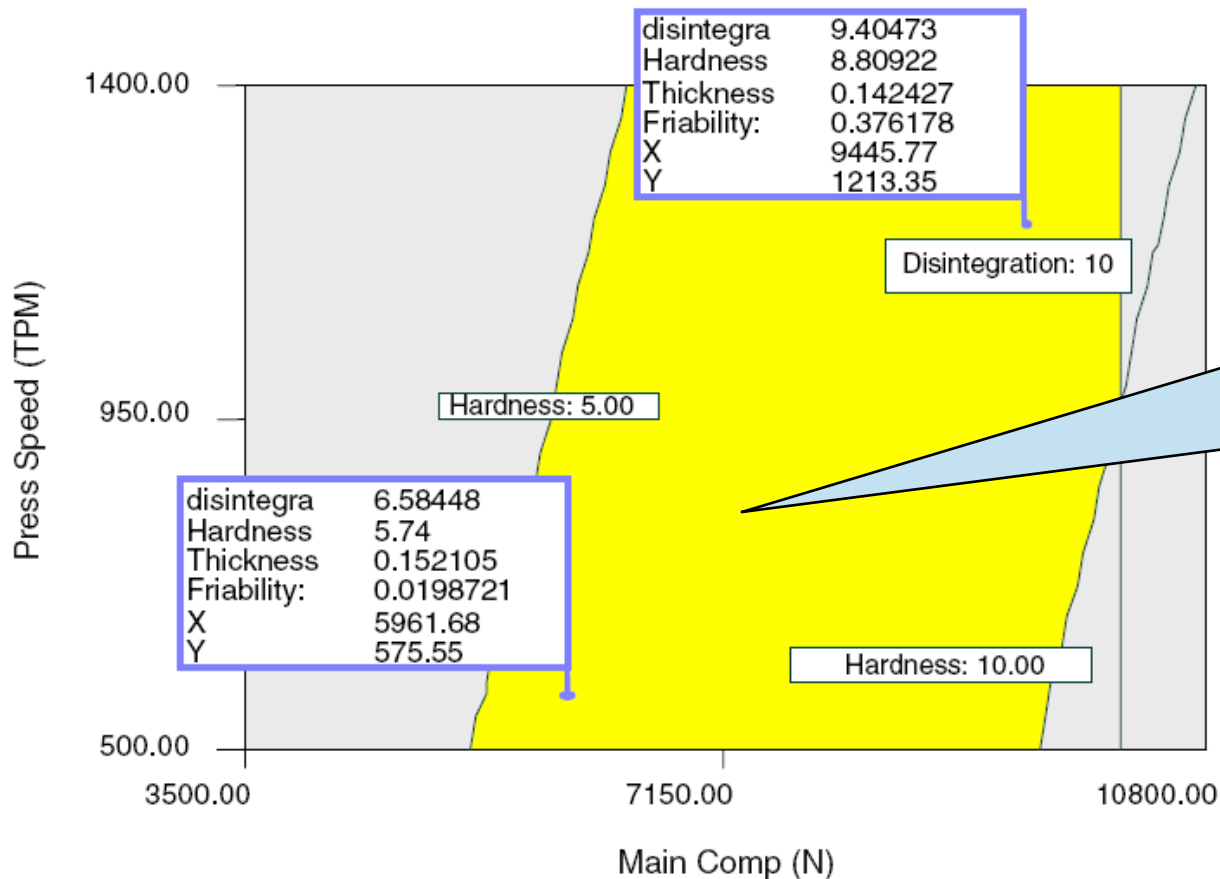
Risk-based approach to Design Space

Design Space Strategy

- **Multivariate Strategy:**
 - multidimensional combination and interaction of material and process variables linked to responses
 - responses comprised of drug product critical-to-quality attributes (CQA)
 - drug products involve a multitude of specifications (response factors)
- **Overcome Limits of Conventional Design Space:**
 - model: predictive response surface
 - model parameters: static variables
 - multiple responses: overlap of mean-response surfaces
- **Apply Bayesian Design Space:**
 - model: posterior predictive probability function
 - model parameters: random variables
 - multiple responses: multivariate joint probability function

Issue with Conventional Design Space

Example of Overlay Plot to Identify Impact of Compression Variables on Tablet Properties



Is the risk of failing to meet all four specifications the same throughout the design space?

J. Lepore and J. Spavins, "PQLI Design Space," *J. Pharmaceutical Innovation* (2008) 3:79-87

Why Multivariate & Bayesian?

- Multivariate because
 - Quality entails multiple responses (CQA defined by specifications)
 - Multiple responses are not independent
 - Correlation between responses can have a big effect on probability of meeting all specifications
- Bayesian because conventional
 - fails to account for uncertainty in model parameters
 - fails to account for correlation structure in data
 - fails to provide a metric for “assurance of quality”
 - fails to enable use of prior information
 - fails to enable adaptive experimental design

Illustrative Example: Process for Coating Polymer

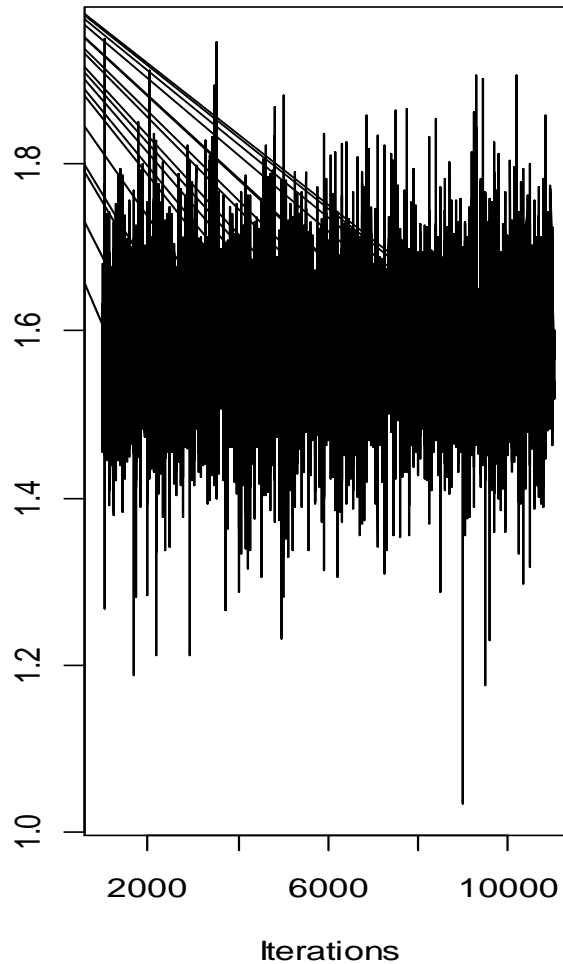
Multivariate Chemical Process

- Chemical Process
 - Production of a coating polymer
 - Two critical to quality attributes (CQA)
 - Response 1: Percent conversion
 - Response 2: Polymer viscosity
 - Two critical process parameters
 - Parameter 1: reaction time
 - Parameter 2: reaction temperature
- Product profile: target CQA
 - Percent conversion: $> 68\%$
 - Viscosity: 40 ± 2 mPA-secs

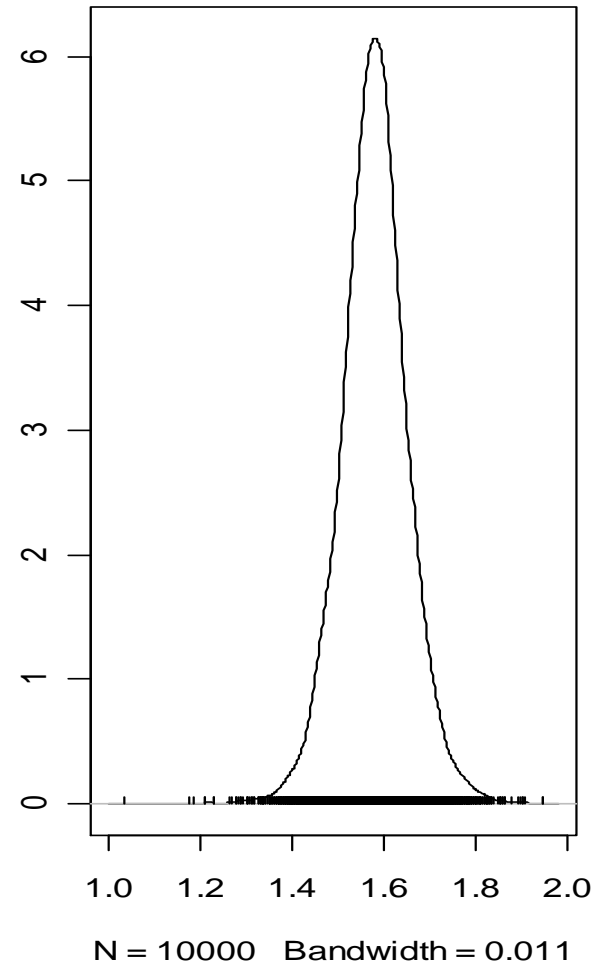
Bayesian Response Surface Model

- Experimental Design
 - Central composite design
 - 8 setting combinations (4 corners and 4 faces of a square)
 - 5 centerpoints
- Models
 - Response surface models for conversion and viscosity
 - linear, cross-product and quadratic terms for each response
- Bayesian Regression and Analysis in R (R-project)

Trace of var1

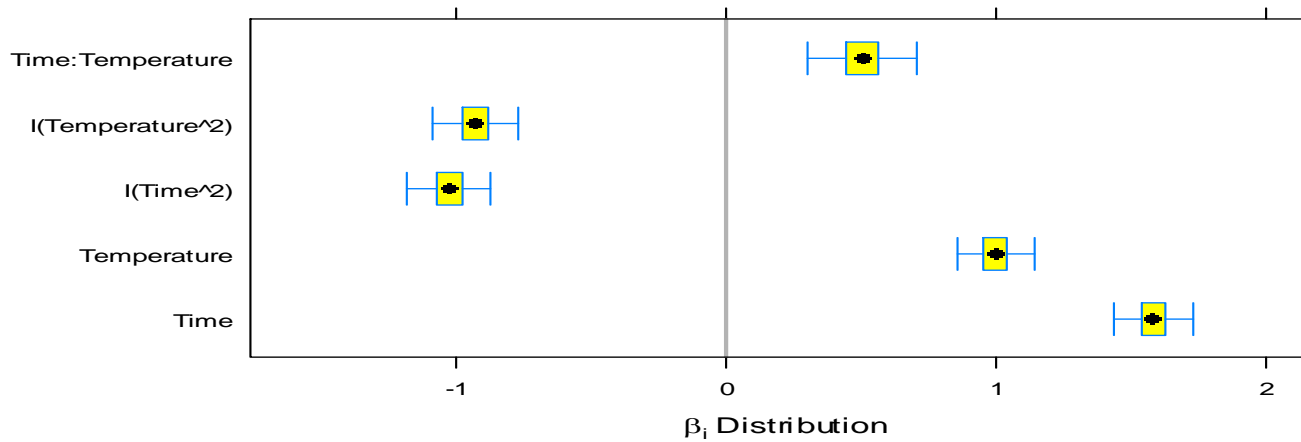


Density of var1

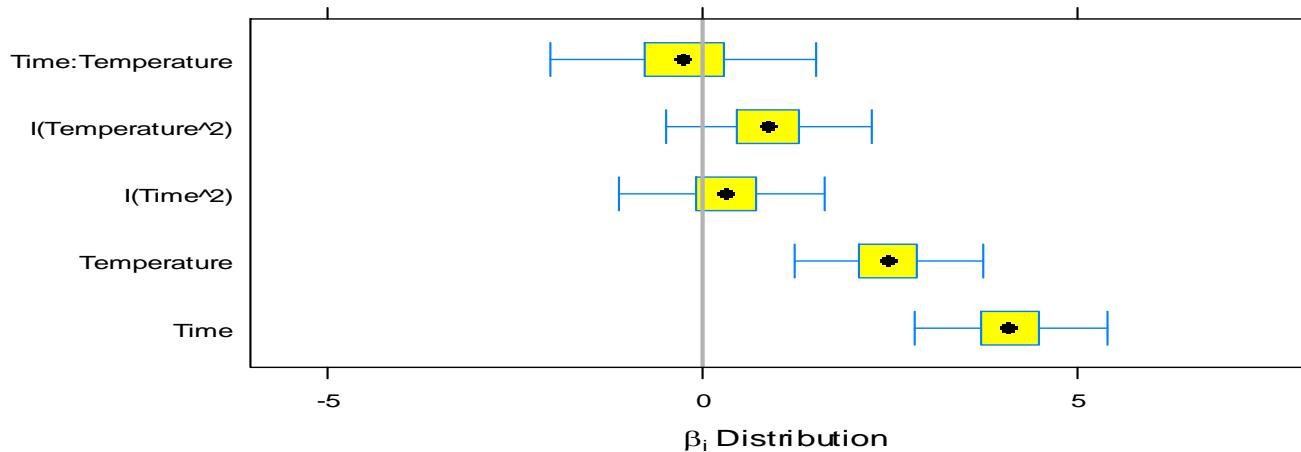


Model Coefficient Distribution

Regression Coefficients: Conversion

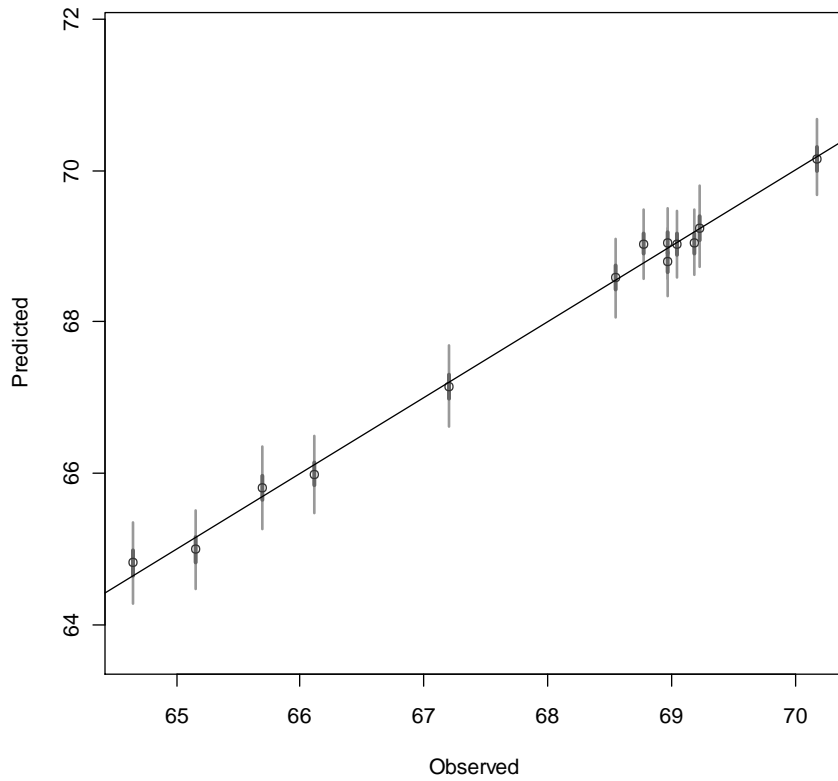


Regression Coefficients: Viscosity

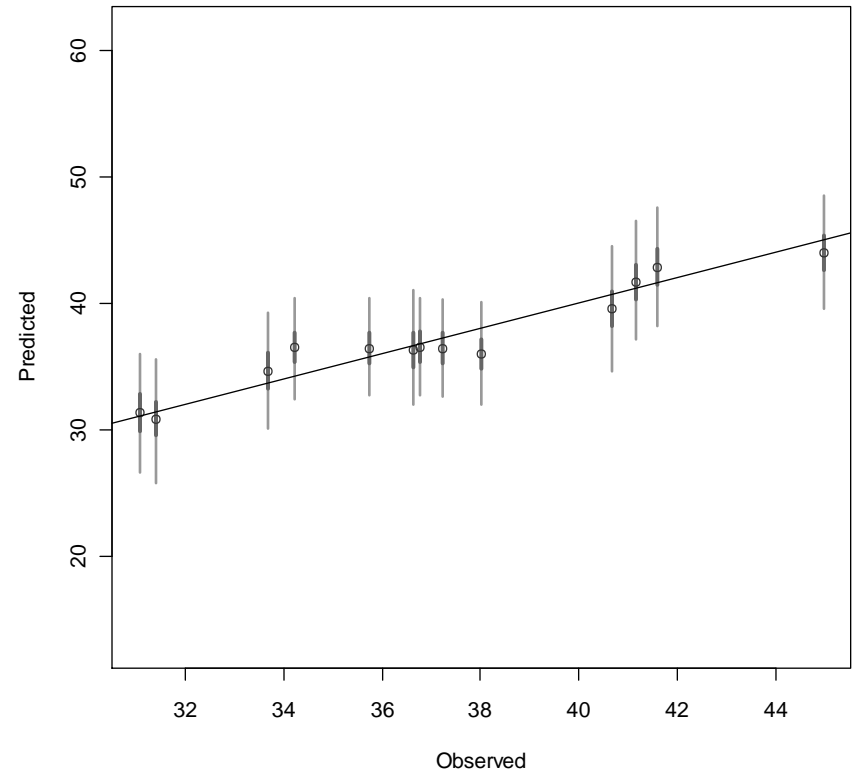


Posterior Distributions

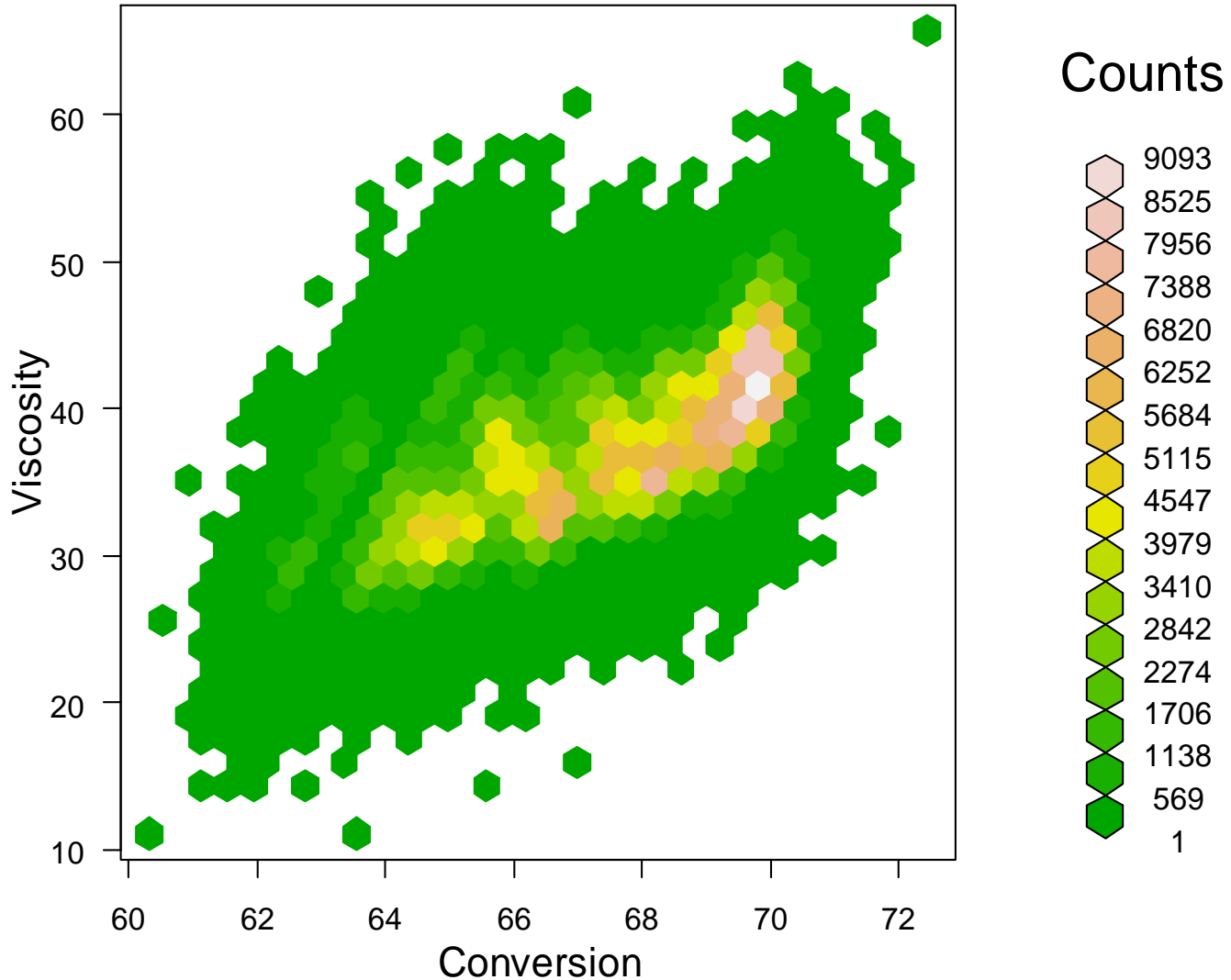
Observed vs. Predicted: Conversion



Observed vs. Predicted: Viscosity

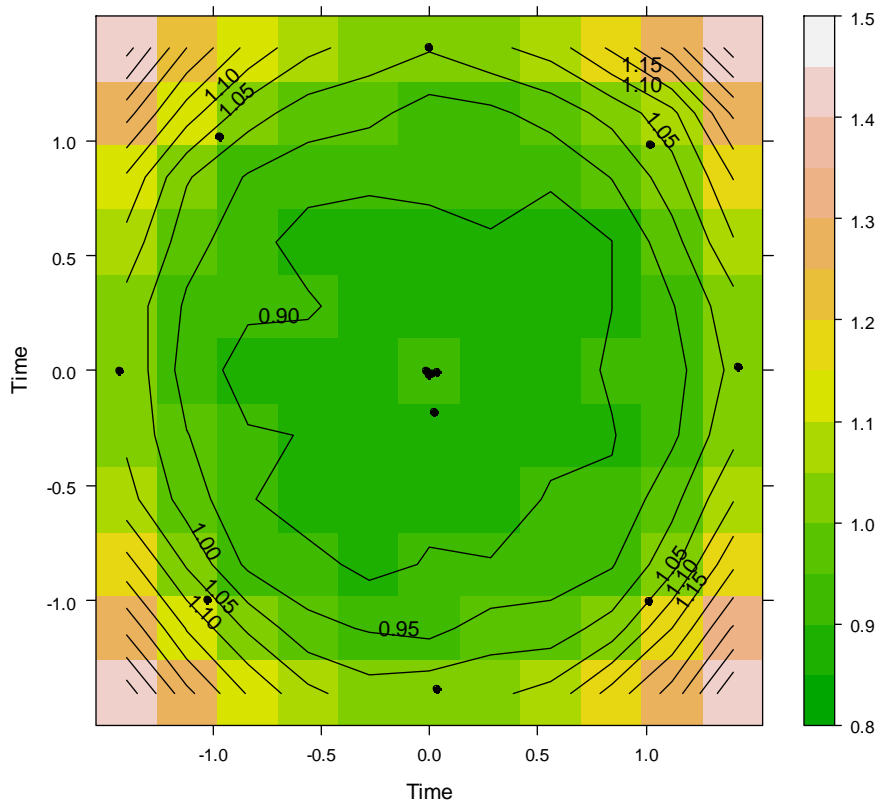


Knowledge Space

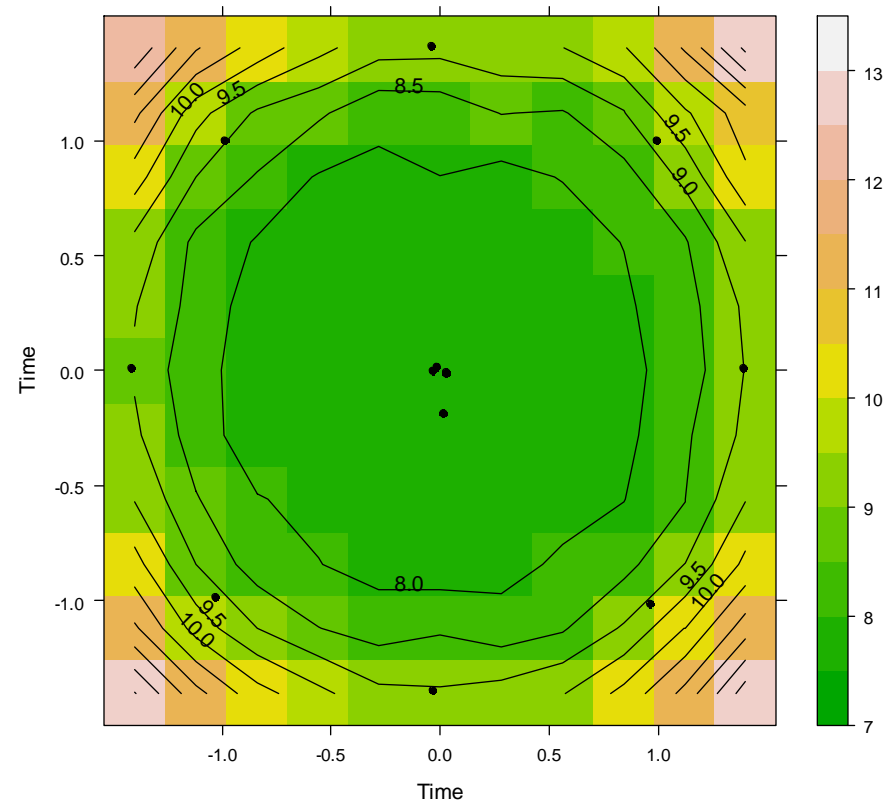


95% Credibility Intervals

Conversion

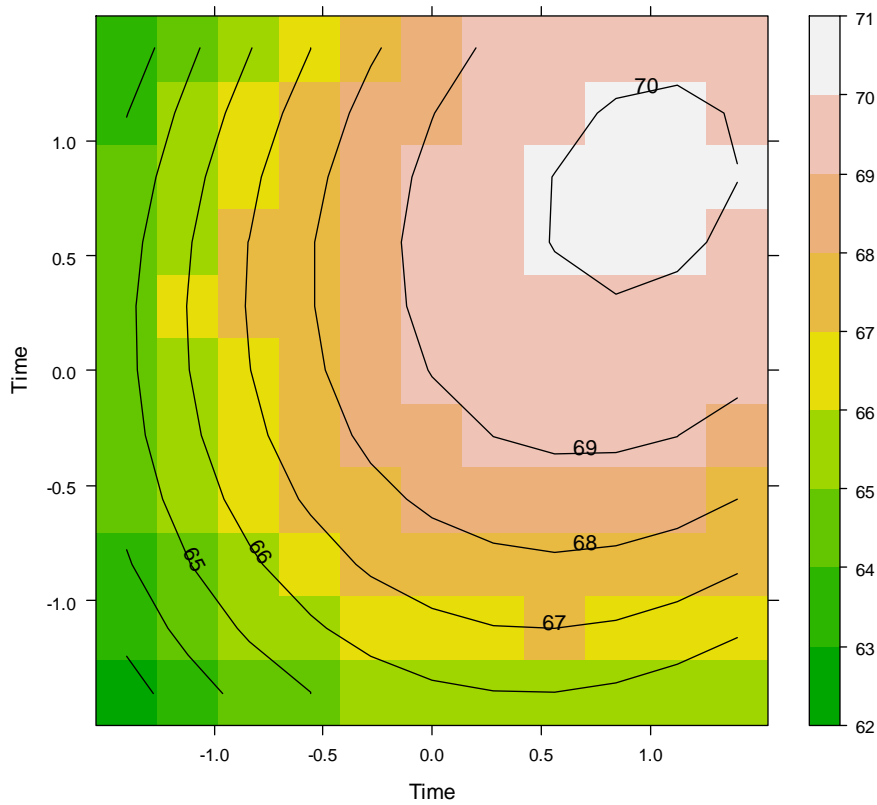


Viscosity

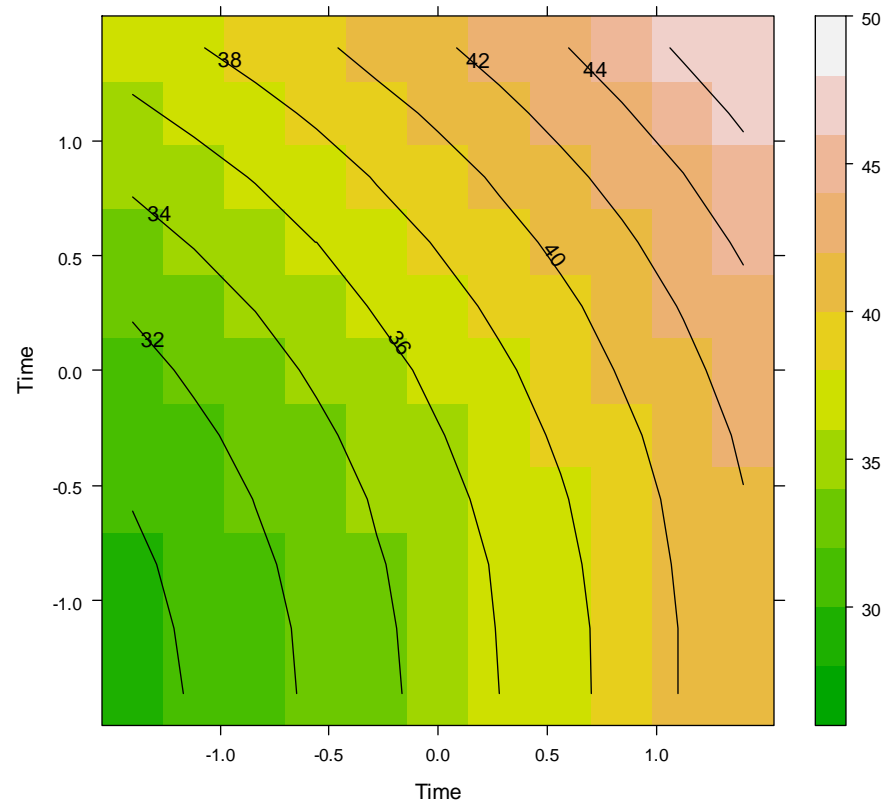


Mean Response Plots

Conversion



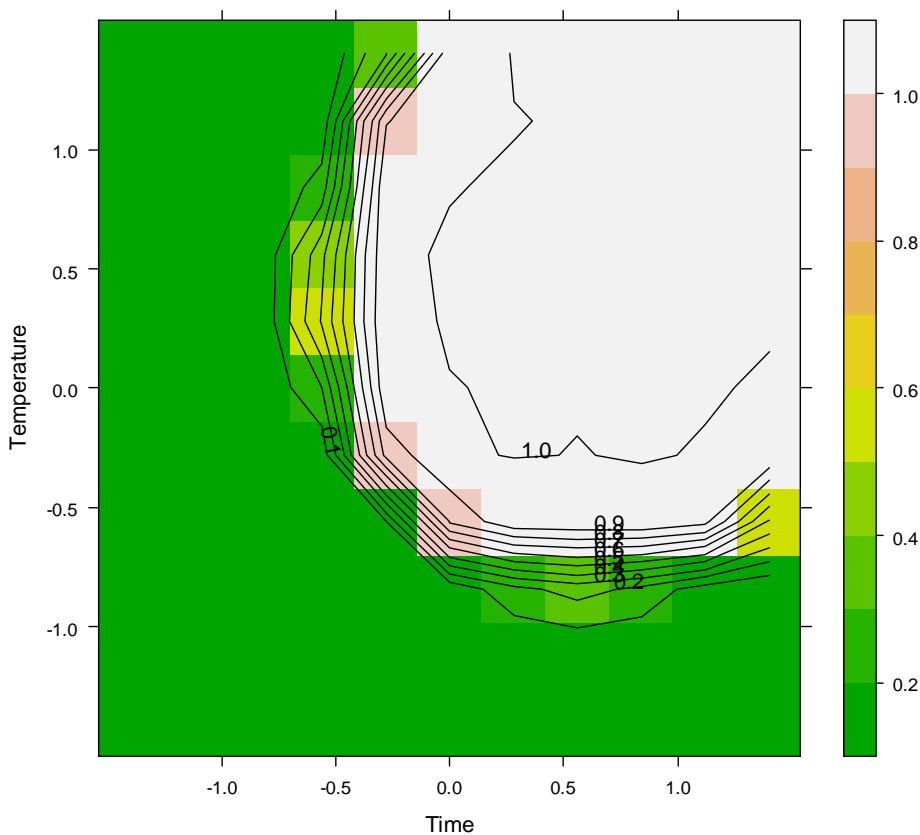
Viscosity



Response Probability Distributions

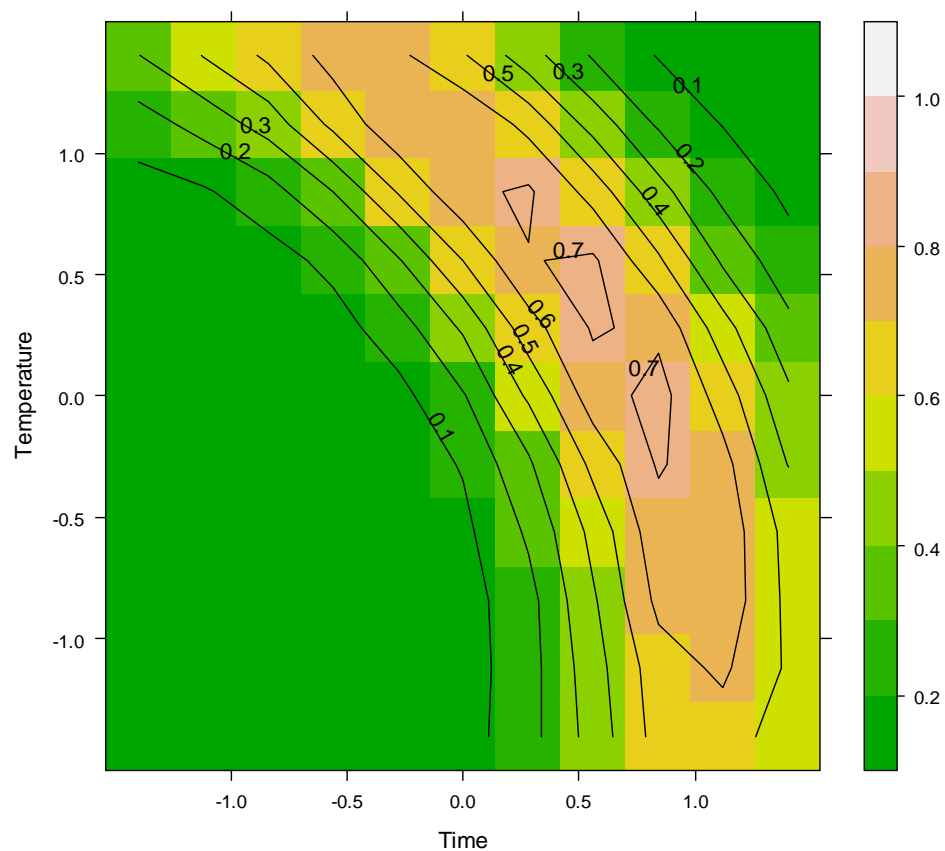
Conversion > 68%

Conversion>68



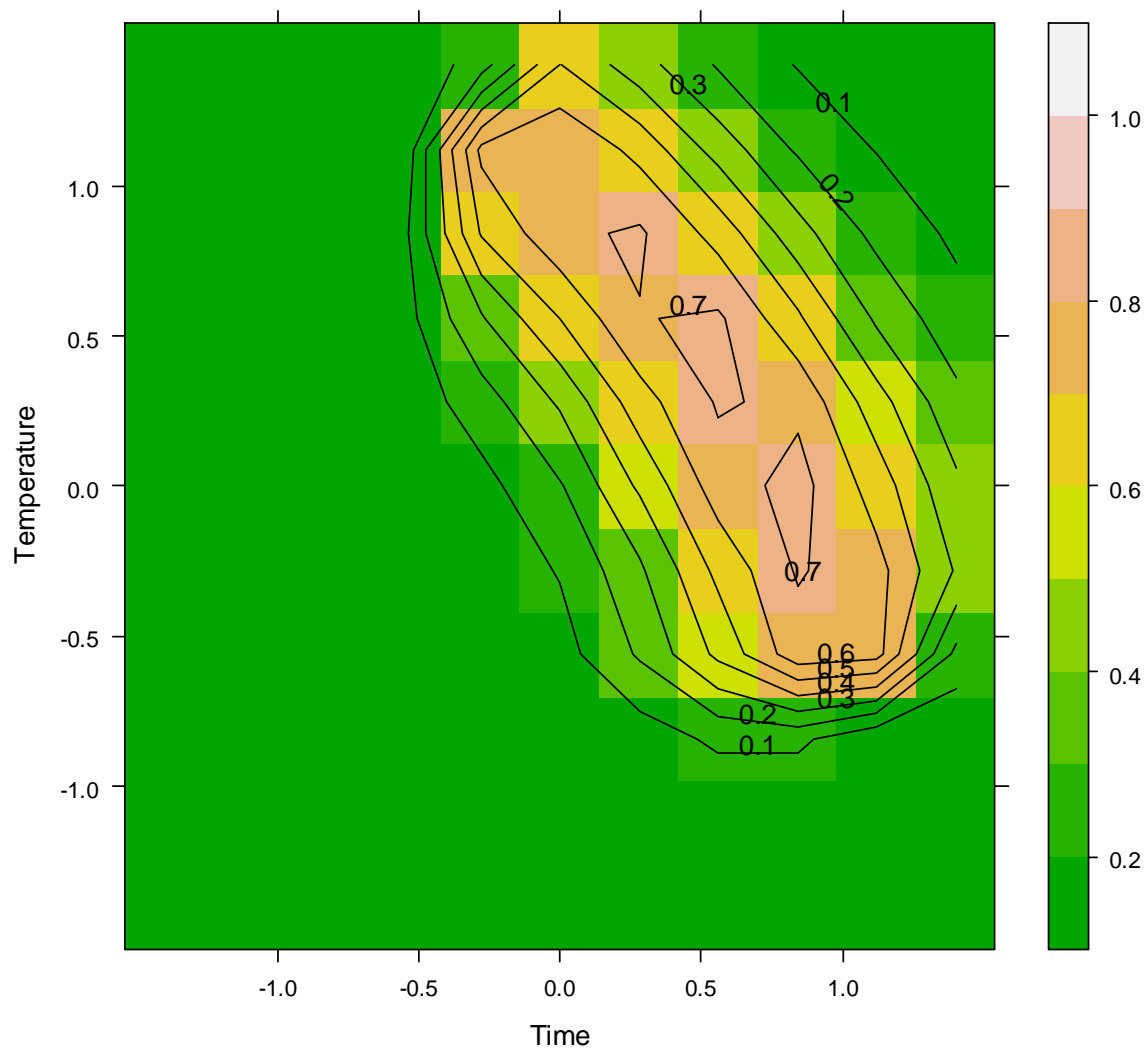
38 < Viscosity < 42

Viscosity>38 & Viscosity<42

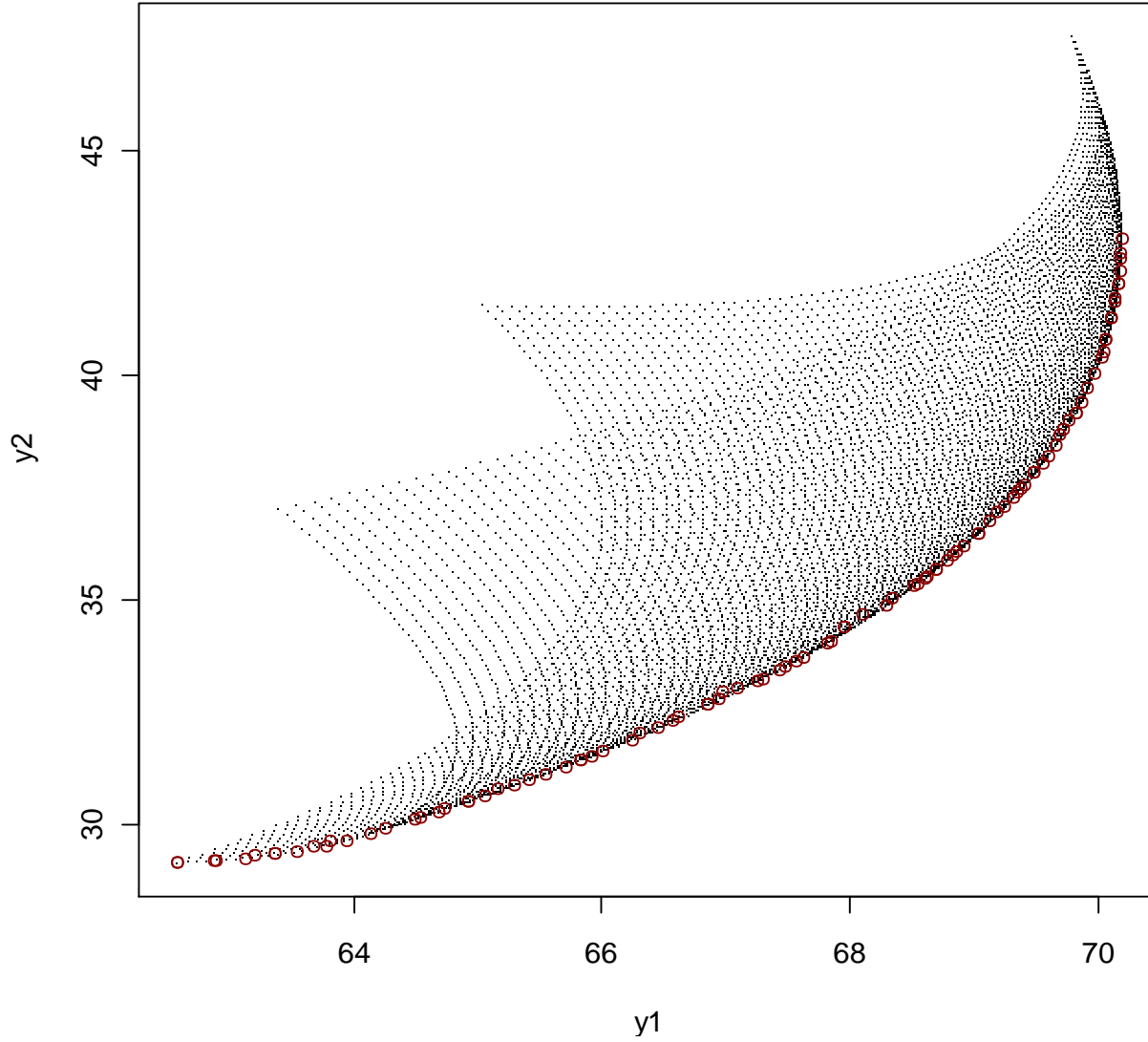


Joint Probability Distribution

Conversion > 68 & Viscosity > 38 & Viscosity < 42

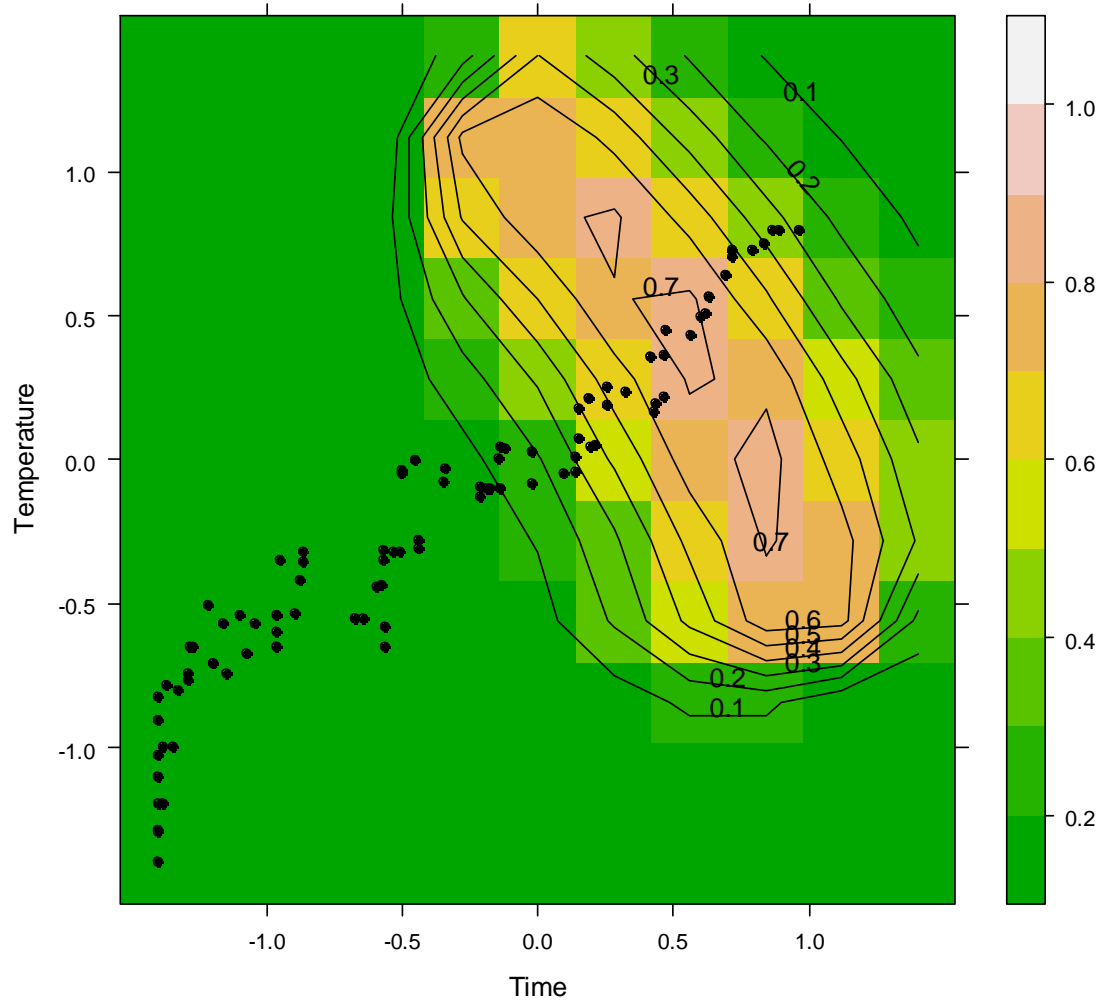


Optimization: Pareto Frontier

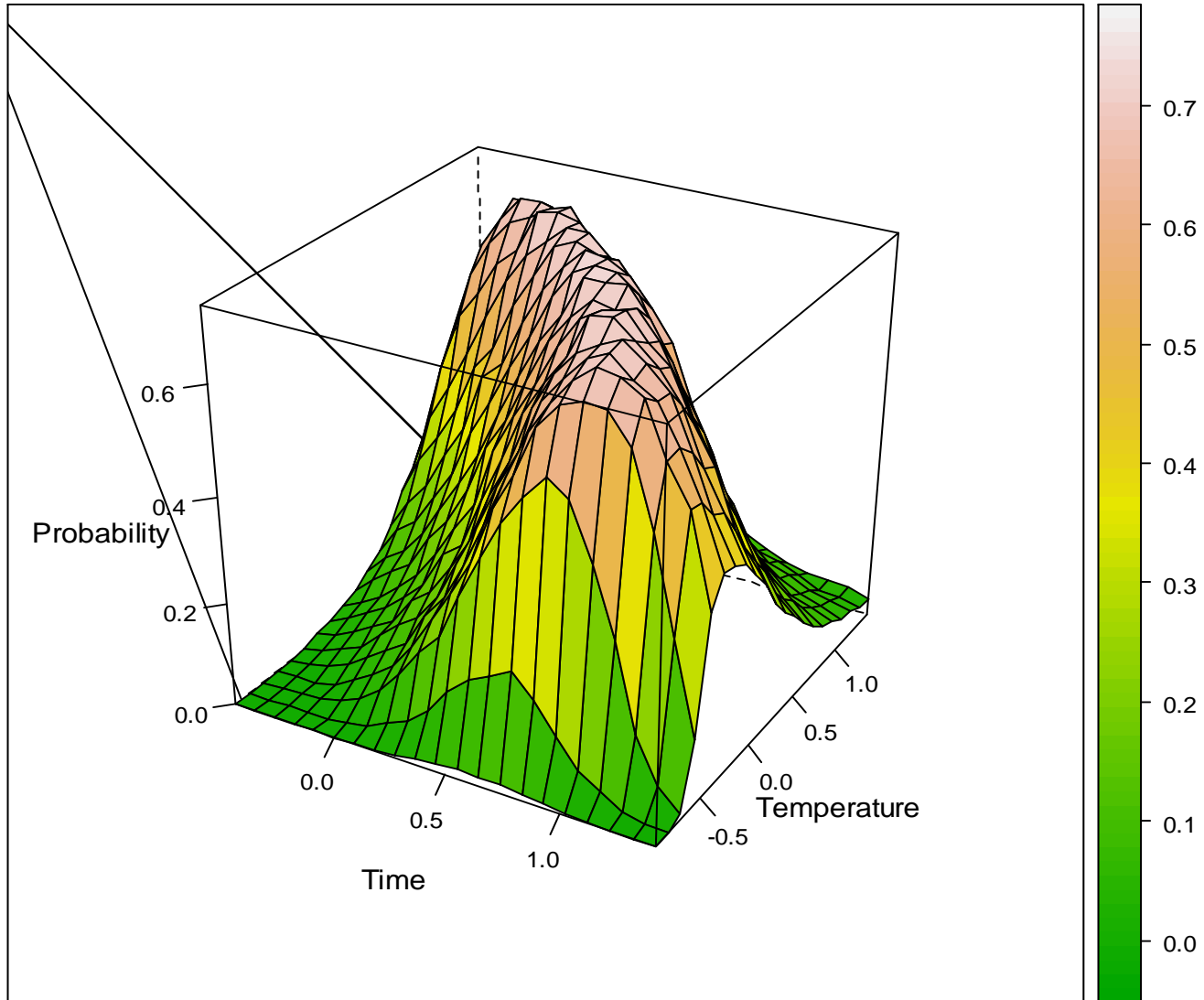


Pareto/Joint Probability Overlay

Conversion>68 & Viscosity>38 & Viscosity<42



50% Credibility Design Space



take-home message

Benefits of Bayesian Approach

- Provides estimates of uncertainty in model parameters.
- Enables use of prior information leading to more efficient adaptive design and experimentation.
- Provides a figure of merit (probability) for meeting product profile (specifications) in terms consistent and easy to understand by technical workers operating in a regulated environment.
- Enables use of Pareto optimization in conjunction with risk minimization.
- Enables a means to establish the reliability of the Design Space.
- Provides a basis for selection of alternate process settings within the design space while ensuring “assurance of quality.”

References

- John J. Peterson (2004). "A posterior predictive approach to multiple response surface optimization." *Journal of Quality Technology*, 36, 139-153.
- John J. Peterson (2008). "A Bayesian approach to the ICH Q8 Definition of Design Space." *Journal of Biopharmaceutical Statistics*, 18, 959-975.

For additional information contact:
Paul van Eikeren, Ph.D.
Paul.van.Eikeren@BlueReference.com

www.InferenceforQbD.com