Analysis of EWS Test Data for Reliability Improvement through Outlier Detection and Automated Ink Map Generation

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Toward "ZERO DEFECTS"

- There is an established relationship between Burn-In failures/ELFs and abnormal devices in the "Bin 1" population
- Quality is inversely proportional to variance
  - Eliminating classified outlier devices from the Bin 1 population will reduce the number of early life failures

Overview

Outlier Detection Technology

- *Confirmed* Parametric and Spatial Outliers
- Automatic Ink Map Update
  - Recipe driven merge
- Yield Impact Analysis
- In-Line Automated System
  - Functional building blocks
- Summary

Outlier Detection Coverage

"PAT" (AEC–Q001–Rev C) Addresses:

- Gaussian Data Distributions

Comprehensive Outlier Detection Addresses:

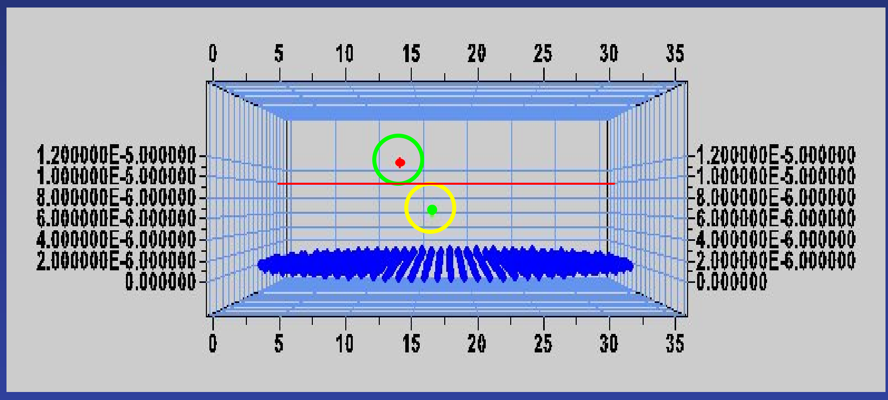
- Any Type of Data Distributions
- Wafer to Wafer Population Shifts
- Test Limit Dependencies (Existence, Location, Cp, Cpk)
- Asymmetric thresholds for control limits
- Classification of detected outliers

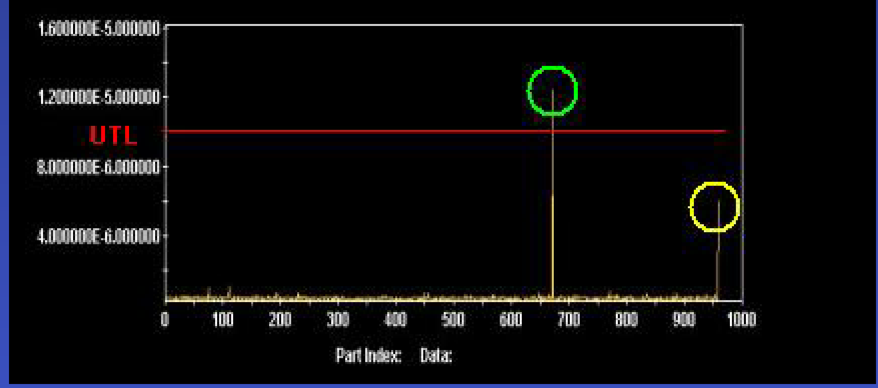
*In **Addition** to Parametric Outlier Detection:*

- Advanced Spatial Outlier Detection Methodologies

Parametric Outlier

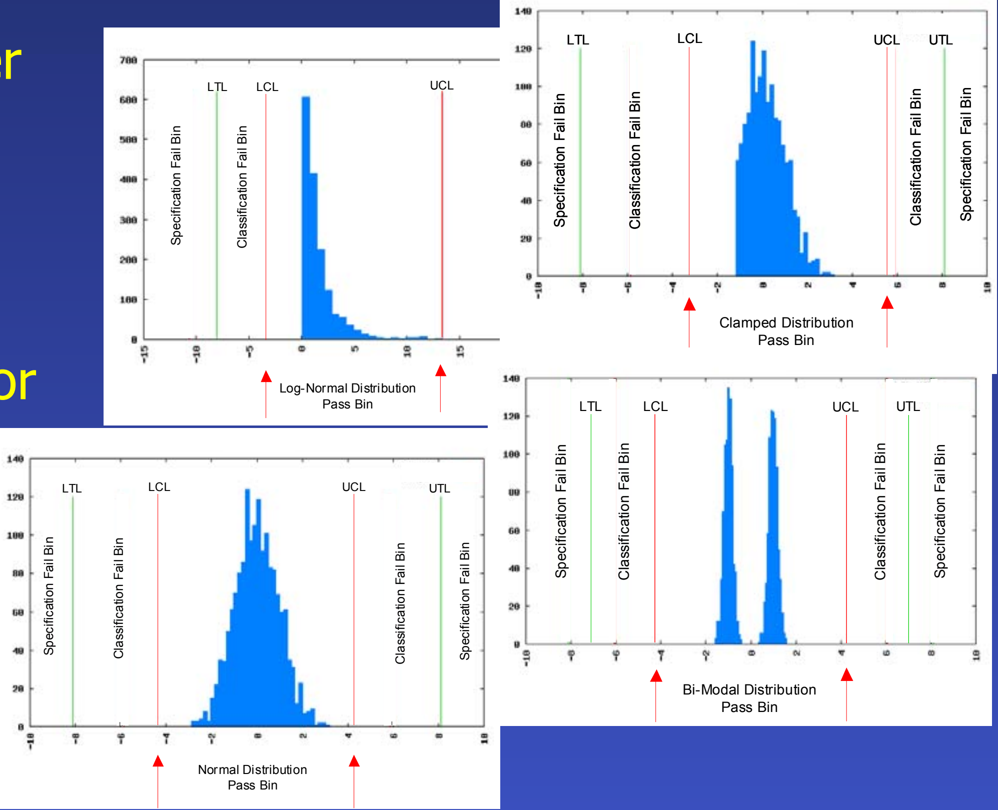
- Test failures – gross outlier removal
- Parametric Outliers – atypical results in Bin 1 population





Data Population Distributions

- **Dynamic determination** of data distribution per wafer/per test based upon skewness, kurtosis and other estimation techniques
- **Automatic selection** of qualified detection algorithm or algorithms for the respective distribution analysis
- Differentiate between Population and Test Limit Outliers, use **asymmetric scaling** factors



Dynamic Outlier Algorithm Selection

Algorithms applied to test/data populations

	Normal (Gaussian)	Log-Normal	Quasi-Categorical	Non Normal
No or invalid test limits	Median Sigma and IQR Distribution only	IQR Distribution only	Median Sigma Distribution only	IQR Distribution only
No or invalid LTL	Median Sigma and IQR Distribution and Test positive	IQR Distribution and Test positive	Median Sigma Distribution and Test positive	IQR Distribution and Test positive
No or invalid UTL	Median Sigma and IQR Distribution and Test negative	IQR Distribution and Test negative	Median Sigma Distribution and Test negative	IQR Distribution and Test negative
Valid test limits	Median Sigma and IQR Distribution and Test	IQR Distribution and Test	Median Sigma Distribution and Test	IQR Distribution and Test

Automatic Outlier Detection Operation

- "On The Fly" Outlier Detection Algorithm Selection defined by Data Population Distribution and Test Limits

TEST	Criteria	Method 1	Method 2	Method 3	Method 4	Method 5	Method 6	OUTLIER_COUNT
T_1400	Rule 3	-	-	USED	USED	USED	USED	1
T_1312	Rule 1	-	-	-	-	USED	USED	1
T_1311	Rule 1	-	-	-	-	USED	USED	1
T_1116	Rule 3	-	-	USED	USED	USED	USED	0
T_1115	Rule 7	-	USED	-	-	USED	-	2
T_1100	Rule 5	USED	-	USED	-	-	-	2
T_515	Rule 1	-	-	-	-	USED	USED	2
T_514	Rule 1	-	-	-	-	USED	USED	1
T_509	Rule 3	-	-	USED	USED	USED	USED	0
T_508	Rule 3	-	-	USED	USED	USED	USED	1
T_17	Rule 8	-	-	USED	USED	-	-	1
T_16	Rule 3	-	-	USED	USED	USED	USED	3
T_15	Rule 13	-	-	-	-	-	-	0

Parametric Outlier Classifications

- Distribution Outliers vs. Test Outliers
  - Conventional techniques are distribution centric
  - Test limits provide additional insight that can improve outlier classification
- Asymmetric thresholds for parametric outlier analysis
- Outlier Magnitudes
  - Large, Medium, Small, Tiny
- Outlier Device Classification
  - Multiple parametric anomalies for the same device

Parametric Outlier Classifications

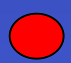
(UTL) 0.005
0.0046
0.0042
0.0038
0.0034
0.003
0.0026
0.0022
0.0018
0.0014
(LTL) 0.001

L
M
S
T
S
M
L

0
140
280
420
560
700
Parts

(L)Data

= Test Limit Failure / Outlier

 = Bin 1 Outlier

Outlier Classification Merge

Recipe Managed Rules

- Outlier Weighting – Magnitude and Frequency
- Specific Tests may be considered uniquely

Example Classification Rules:

CRITICAL="L > 0 or M > 4"

MARGINAL="M ≥ 2 or S > 10"

Device	Test 1	Test 2	Test 3	# T	# S	# M	# L
10,11	T	M	L	1	0	1	1
10,12	M	-	M	0	0	2	0

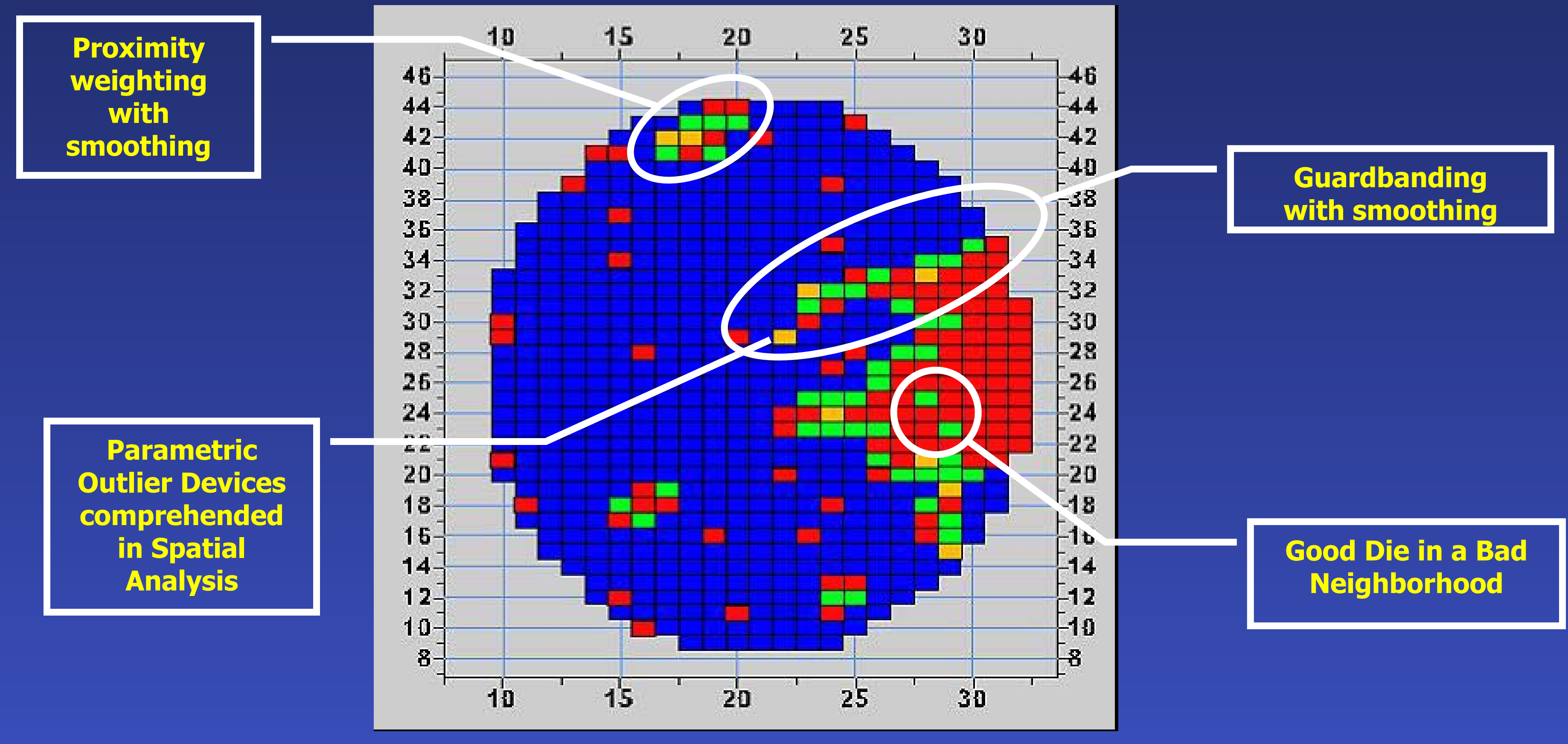
Results:

- Device 10,11 is classified as CRITICAL = Bin 20
- Device 10,12 is classified as MARGINAL = Bin 10

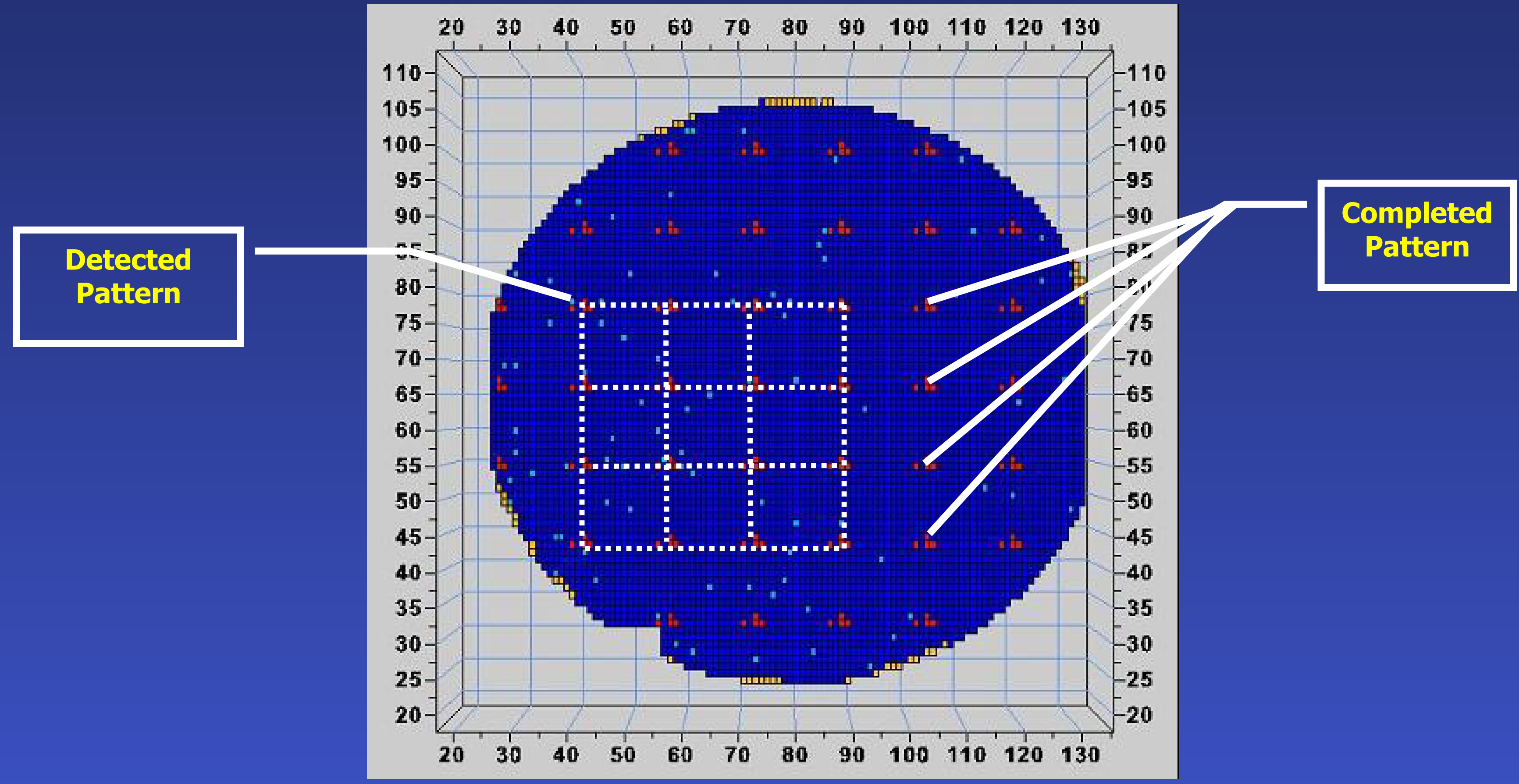
Spatial Outlier Detection

- Recipe-driven downgrading of devices based on proximity to Failing and Outlier Devices
- Measurably Reduce ***Full-Wafer Scrap*** and ensure reliability of "Bin 1" die
- Configurable and flexible methods controlled via user-defined recipes
- User-defined sensitivity and proximity techniques driven by process, product, and quality policy

Geographic Analysis Application



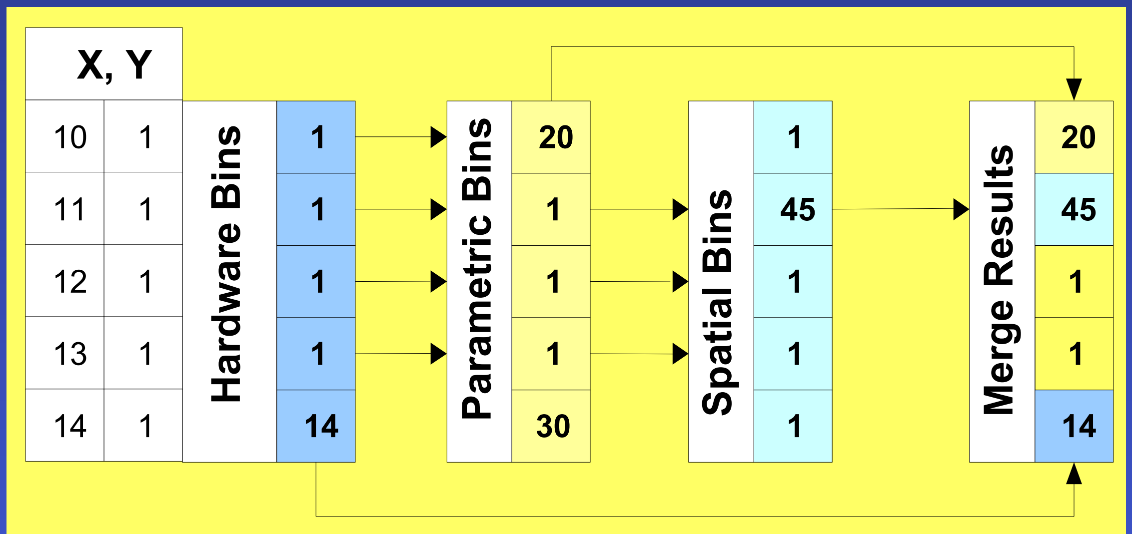
Stepper and/or Repeating Pattern



Wafer Data Merge Process

Recipe Managed Rules

- Parametric outlier classification results and spatial analysis map(s)
- Merge all datasets together based on user defined merge priority

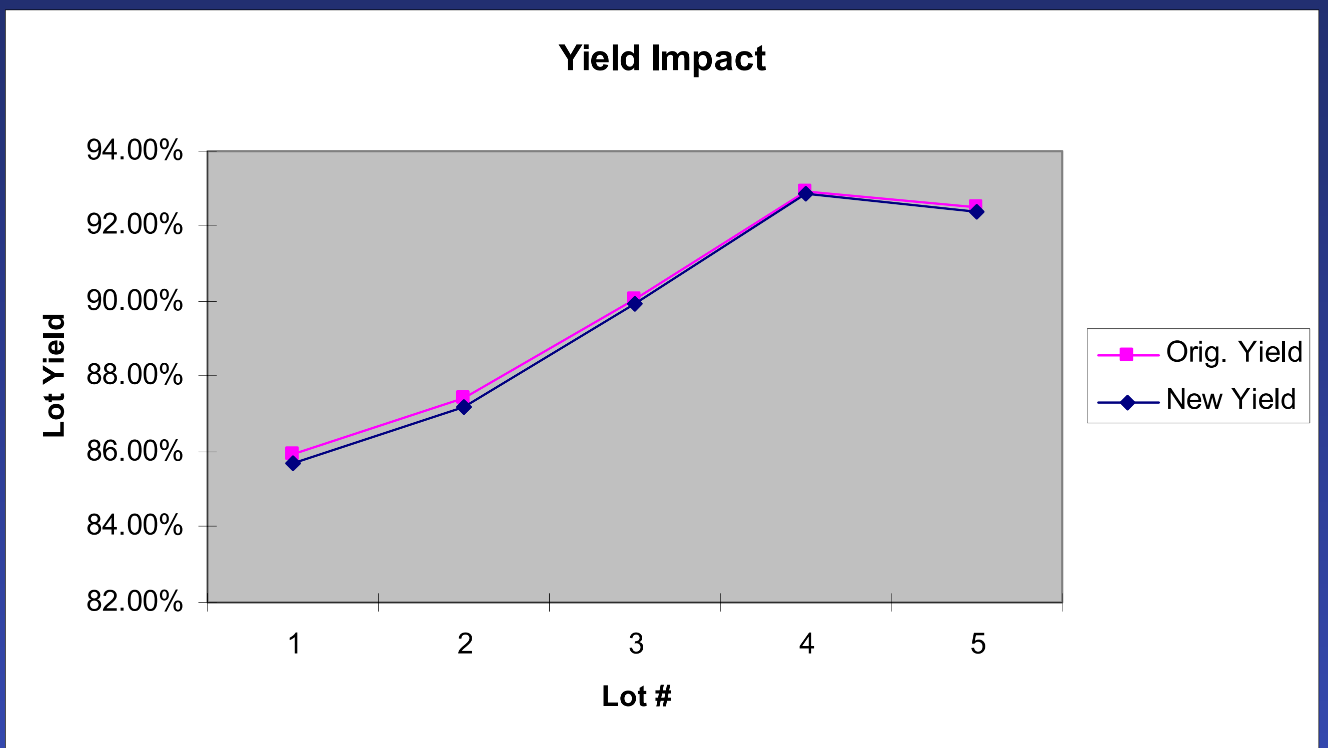


Wafer Merge Results

Tester Bin Results

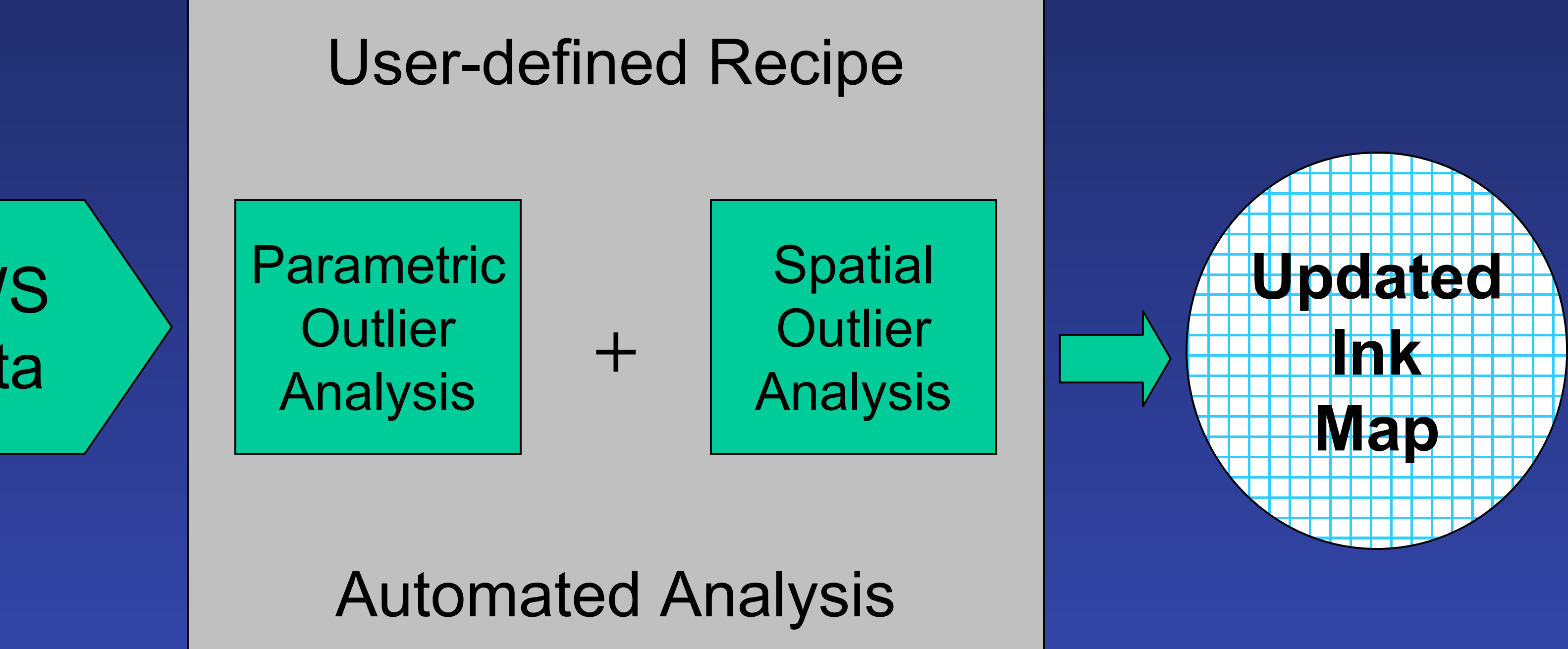
Final Merged Results

What is the Impact to Yield ?



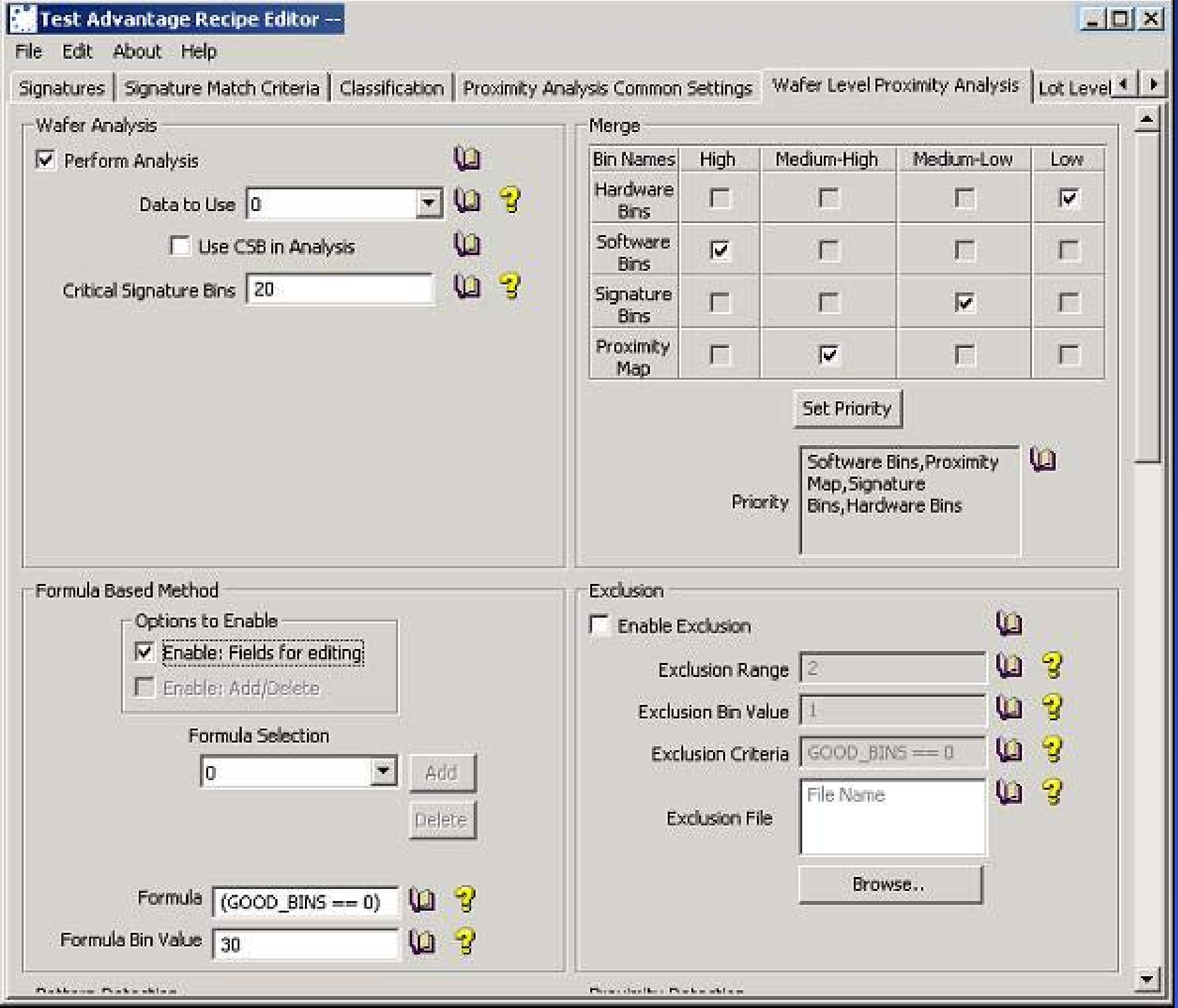
Lot	Parts	Fails	Critical	Proximity	Orig Yield(%)	New Yield(%)	Delta(%)
1	23064	3249	26	16	85.91	85.73	0.18
2	22103	2784	42	5	87.40	87.19	0.21
3	19220	1914	15	6	90.04	89.93	0.11
4	23064	1627	24	0	92.95	92.84	0.10
5	23064	1731	23	0	92.49	92.40	0.07
	110515	**11305**	**130**	**27**	**89.77**	**89.63**	**0.14**

Functional Building Blocks



Objectives:
- In-Line
- Automated
- 100% of the Data is Analyzed

Menu Driven Recipe Management Approach



Toward *Zero Defect* Production

- Identification and rules-based classification of Parametric Outliers in any type of test data distribution
- Rules-based Spatial Outlier detection
- Maximum outlier detection coverage
- Rules-based classification and merge identifying "Qualified" Device Outliers
- Managed Yield vs. DPPM
- 100% data analysis by a fully integrated and automated in-line production system