Title:

A Physics-Based State Conformance Engine for Thin-Film Structural Deviation Detection

by Stephen Francis, founder of Phocoustic, Inc., February 24, 2026

Abstract

Modern thin-film and structured-surface inspection systems are typically framed as anomaly detection pipelines that rely on probabilistic inference derived from learned data distributions. While effective in certain contexts, such approaches lack deterministic traceability, physical interpretability, and calibration stability required in high-precision manufacturing environments. This work introduces a deterministic inspection architecture composed of a State Conformance Framework (SCF) and a State Convergence Engine (SCE), replacing probabilistic anomaly scoring with physics-grounded state measurement and convergence evaluation.

The State Conformance Framework defines surface state as a structured vector in deterministic conformance space composed of measurable spatial, directional, spectral, and temporal components. These include Spatial Topology Response Tracking (STRT), which localizes deviation through structured partitioning; Directional Integrity Field (DIF), which evaluates coherence of drift vectors; Structured Drift Flux (SDF), which integrates directional drift accumulation across the domain; Drift Acceleration Index (DAI), which measures first- and second-order temporal derivatives of structured drift metrics; Physics-Anchored Drift Reduction (PADR); and Spectral Loss Extension (SLE), which quantifies high-frequency spectral attenuation associated with thin-film redistribution or micro-texture collapse. Together, these components yield a deterministic conformance vector relative to one or more validated reference states.

Building upon SCF, the State Convergence Engine evaluates proximity, trajectory, and stabilization behavior within this conformance space. Rather than merely identifying deviation, SCE determines whether an observed surface is converging toward, diverging from, or stabilizing within admissible tolerance envelopes associated with validated physical states. This enables deterministic multi-reference state membership evaluation without reliance on trained defect classes or probabilistic classification.

Validation was performed using a controlled laboratory surrogate experiment involving isopropyl alcohol deposition on a matte Astariglass substrate under fixed darkfield illumination. The resulting coffee-ring formation produced spatially localized boundary gradients, interior haze, and measurable spectral redistribution. The SCF architecture separated conformant baseline and redistributed states across spatial, directional, spectral, and temporal axes. The SCE layer further confirmed stabilization

and convergence behavior following surface cleaning, demonstrating deterministic state recovery verification.

Results demonstrate that physically meaningful surface transitions manifest as structured multi-axis displacement and trajectory within a bounded conformance manifold. The combined SCF–SCE architecture reframes inspection as deterministic state verification and convergence evaluation rather than probabilistic anomaly inference. This approach supports auditability, calibration stability, process accountability, and early instability forecasting, and is directly applicable to semiconductor processing, coating validation, PCB inspection, and thin-film metrology.

The proposed framework establishes a physics-anchored alternative to machine-learning-first inspection systems, enabling interpretable, scalable, and deterministic surface state validation and convergence assessment.

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1. Executive Summary

The Problem: Detecting Structural State Deviation in Thin Films

Modern thin-film inspection systems face a fundamental challenge: reliably determining whether a surface remains in its intended physical state. In manufacturing, cleaning validation, semiconductor processing, and materials research, the question is not merely whether something appears “unusual,” but whether the observed scattering field conforms to a defined, expected physical condition.

Thin films and surface perturbations often manifest as subtle changes in optical scattering behavior. These changes may include localized deposition rings, distributed haze, boundary-layer gradients, or directional stress-induced drift. Traditional inspection approaches frequently struggle to distinguish meaningful structural deviation from lighting variation, sensor noise, or benign texture differences. As a result, detection may be inconsistent, over-sensitive, or dependent on large training datasets.

The core problem, therefore, is not anomaly identification in the statistical sense—it is deterministic verification of state conformance under physically grounded criteria.

Limitations of Machine-Learning-First Systems

Most contemporary vision systems are framed as anomaly detection engines. They learn distributions of "normal" from historical datasets and flag deviations probabilistically. While powerful in certain contexts, this approach presents several limitations in thin-film and structured-surface domains:

- **Training Dependence:** Performance depends on representative training data. Subtle surface states not seen during training may be misclassified.
- **Probabilistic Output:** Results are typically confidence scores rather than physically interpretable deviation metrics.
- **Opacity:** Deep models often lack explainability, making root-cause analysis difficult.
- **Baseline Ambiguity:** "Normal" is statistically inferred rather than physically defined.

In high-precision environments—such as wafer inspection, coating validation, or process verification—engineers require measurement repeatability, calibration stability, and traceable deviation metrics. A black-box anomaly score is insufficient when compliance, tolerance thresholds, and process accountability are required.

Proposed Solution: Deterministic Drift + Topology + Directionality

This work introduces a deterministic State Conformance architecture built on three physically anchored principles:

1. **Drift Quantification** – Measure deviation relative to a defined, captured reference state.
2. **Topological Localization** – Identify where deviation occurs within structured spatial partitions.

3. **Directional Coherence Assessment –** Determine whether deviation exhibits physically meaningful structure.

Rather than asking, “Is this unusual?”, the system asks:

- Does the observed scattering field conform to the defined baseline?
- Where does deviation emerge?
- Is the deviation structurally organized or stochastic?
- Is deviation persisting, stabilizing, or accelerating?

This reframing shifts the epistemological stance from probabilistic anomaly inference to measurable state verification.

Key Contributions

STRT – Spatial Topology Response Tracking

STRT partitions the observed surface into structured spatial tiles and evaluates each tile relative to a defined reference state. It provides:

- Geographic localization of deviation
- Quantification of magnitude per region
- Boundary and cluster mapping
- Topological distribution analysis

STRT transforms deviation from an abstract scalar into a spatially accountable structure.

DIF – Directional Integrity Field

Once STRT identifies regions of deviation, DIF characterizes their internal structure. It evaluates:

- Vector orientation coherence
- Drift direction stability
- Reinforcement versus stochastic behavior
- Energy gradient alignment

Physically meaningful state change typically produces directional coherence; transient noise does not. DIF therefore distinguishes structural instability from random variation.

DAI – Drift Acceleration Index

DAI extends spatial and directional analysis into the temporal domain. It measures first- and second-order derivatives of structured drift metrics to determine:

- Instability growth rate
- Acceleration of structural change
- Early-stage transition behavior

Persistent positive drift acceleration indicates accumulating instability before visible macroscopic failure. DAI transforms state conformance from static measurement into dynamic monitoring.

Summary of Laboratory Demonstration

Astariglass Matte Surface + IPA Ring Deposition

A controlled experiment was conducted using a matte Astariglass surface subjected to an isopropyl alcohol (IPA) deposition event, producing a characteristic “coffee-ring” structure with interior haze.

The scene naturally separated into three topological regions:

1. **Exterior Reference Region –** Nominal baseline surface
2. **Ring Boundary Band –** High-gradient transition zone
3. **Interior Haze Region –** Distributed thin-film perturbation

Results demonstrated:

- STRT successfully localized deviation to the ring boundary and interior region while preserving exterior conformance.
- DIF identified strong directional structure at the boundary band, consistent with evaporative transport physics.
- Interior haze exhibited distributed but coherent low-magnitude drift distinguishable from background noise.
- DAI showed measurable temporal stabilization following evaporation, confirming state transition behavior rather than transient fluctuation.

Importantly, when the surface was cleaned and returned to baseline, the system confirmed null deviation—demonstrating positive conformance verification rather than mere anomaly absence.

Conclusion

This work reframes surface inspection from anomaly detection to **State Conformance Verification**.

By integrating spatial localization (STRT), directional coherence analysis (DIF), and temporal acceleration modeling (DAI), the system provides:

- Deterministic deviation metrics
- Physically interpretable outputs
- Spatial accountability
- Directional structure validation
- Early instability forecasting

The result is a structured conformance engine suitable for thin-film validation, semiconductor inspection, coating verification, and precision process control.

Rather than estimating the probability of abnormality, the system confirms adherence to expectation—or quantifies precisely how and where conformance is lost.

The SCF vector formulation corresponds to the persistence-weighted drift flux and directional instability modeling disclosed in U.S. Application No. 19/395,483 and related filings.

2. State Conformance Framework (SCF): Deterministic Measurement Architecture

State Conformance is defined as the formal evaluation of whether an observed physical system remains within its expected structural, spectral, and topological bounds over time. While anomaly detection focuses on identifying deviations from nominal patterns, State Conformance establishes a broader verification and governance framework in which anomaly detection becomes a special case of structured deviation analysis. In this model, conformity assessment, tolerance validation, drift persistence, and distributed perturbation tracking are treated as measurable states within a unified architecture. The system therefore supports measurement-driven oversight and process governance without presupposing direct actuation or closed-loop control.

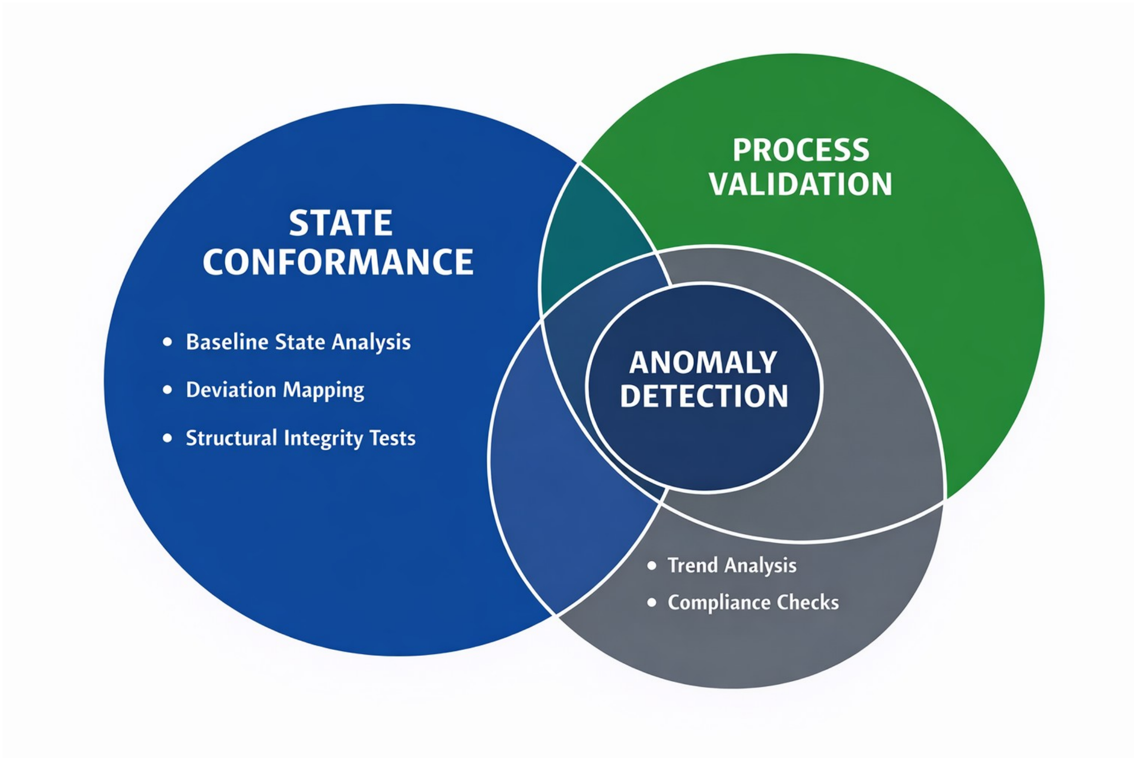

Figure 1 — Conceptual Relationship Between State Conformance and Anomaly Detection. Anomaly detection represents a subset operational mode within the broader State Conformance framework. State Conformance additionally encompasses tolerance validation, structured drift measurement, persistence modeling, and distributed perturbation analysis.

2.1 Definition

State Conformance is defined as a deterministic, multi-dimensional measurement of physical adherence relative to one or more validated reference states within structured conformance space.

The State Conformance Framework (SCF) produces a structured conformance vector:

v(t)=f(STRT(t), DIF(t), SDF(t), DAI(t), PADR(t), SLE(t))\mathbf{v}(t) = f\big(\text{STRT}(t),\, \text{DIF}(t),\, \text{SDF}(t),\, \text{DAI}(t),\, \text{PADR}(t),\, \text{SLE}(t) \big)v(t)=f(STRT(t),DIF(t),SDF(t),DAI(t),PADR(t),SLE(t))

where:

- **STRT** — Spatial Topology Response Tracking
- **DIF** — Directional Integrity Field
- **SDF** — Structured Drift Flux
- **DAI** — Drift Acceleration Index
- **PADR** — Physics-Anchored Drift Regulation

- **SLE** — Spectral Loss Energy

The SCF output is the structured conformance vector v(t)\mathbf{v}(t)v(t).

The function f(·)f(\cdot)f(·) is not a probabilistic classifier. It is a deterministic aggregation mechanism that integrates spatial localization, directional structure, accumulated drift flux, temporal evolution, amplitude persistence, and spectral redistribution into a unified geometric representation of surface state.

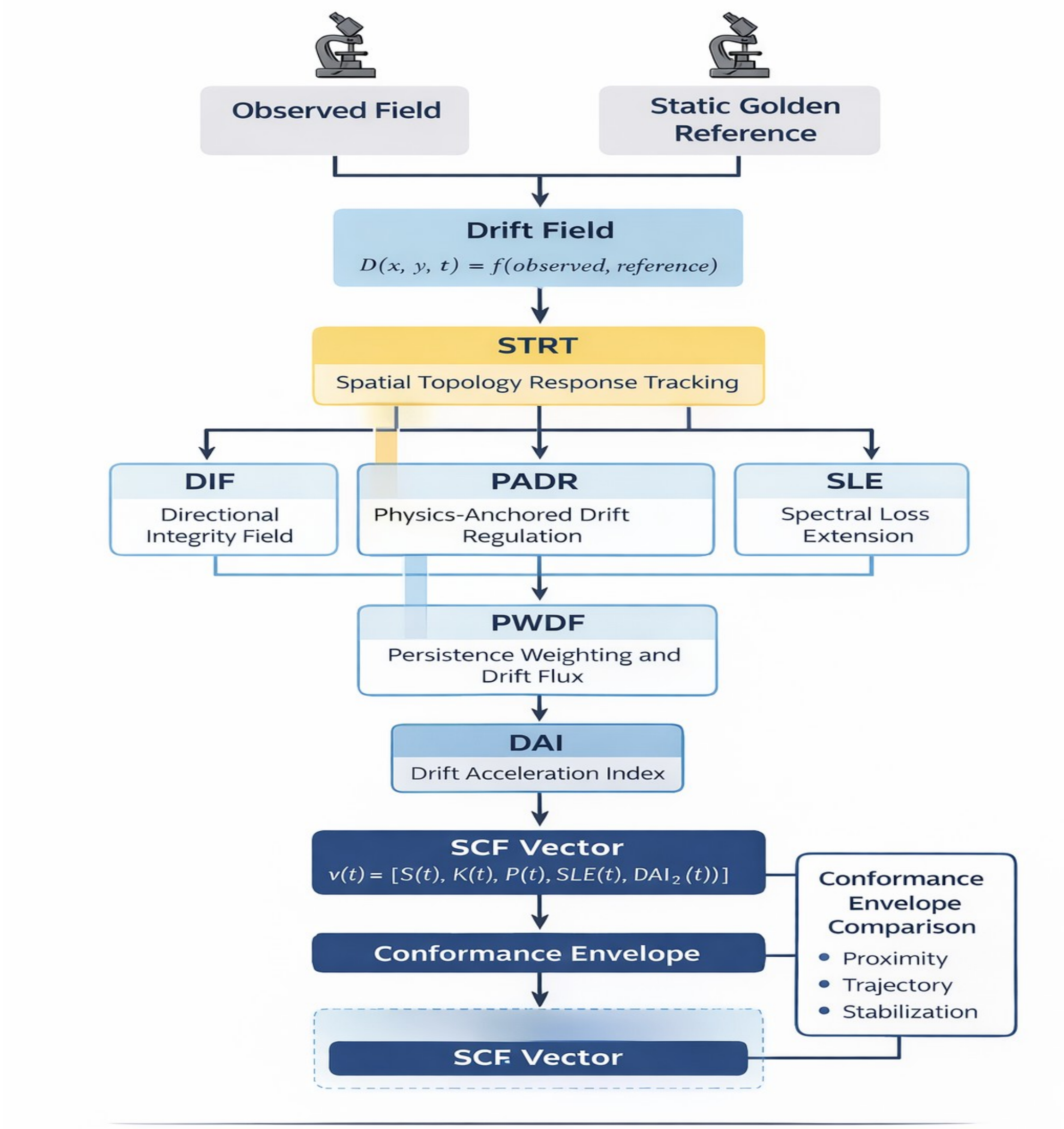

Figure 2 — State Conformance Engine Verification Stack

Hierarchical integration of STRT (Spatial Reference Tiling), DIF (Directional Instability Field), DAI (Drift Acceleration Index), PADR (Physics-Anchored Drift Reduction), and SLE (Spectral Loss

Estimation) within the State Conformance Engine (SCE). The stack converts localized spatial deviation into directionally structured, persistence-validated, temporally modeled, and spectrally characterized drift metrics, enabling deterministic confirmation or quantification of physical state conformance.

Unlike conventional anomaly-detection pipelines, SCF does not estimate abnormality likelihood. Instead, it computes the measurable position of the observed surface within conformance space.

The structured conformance vector v(t)\mathbf{v}(t)v(t) encodes:

- The spatial distribution of measurable deviation
- The magnitude and persistence of drift
- The directional organization of structural change
- The temporal trajectory of instability (growth, stabilization, or acceleration)
- The presence of spectral energy redistribution consistent with material state transition

State Conformance is therefore a measurement construct grounded in deterministic drift geometry. It defines state position without probabilistic inference. Evaluation of proximity, admissibility, and convergence relative to validated reference states is performed separately by the State Convergence Engine (SCE).

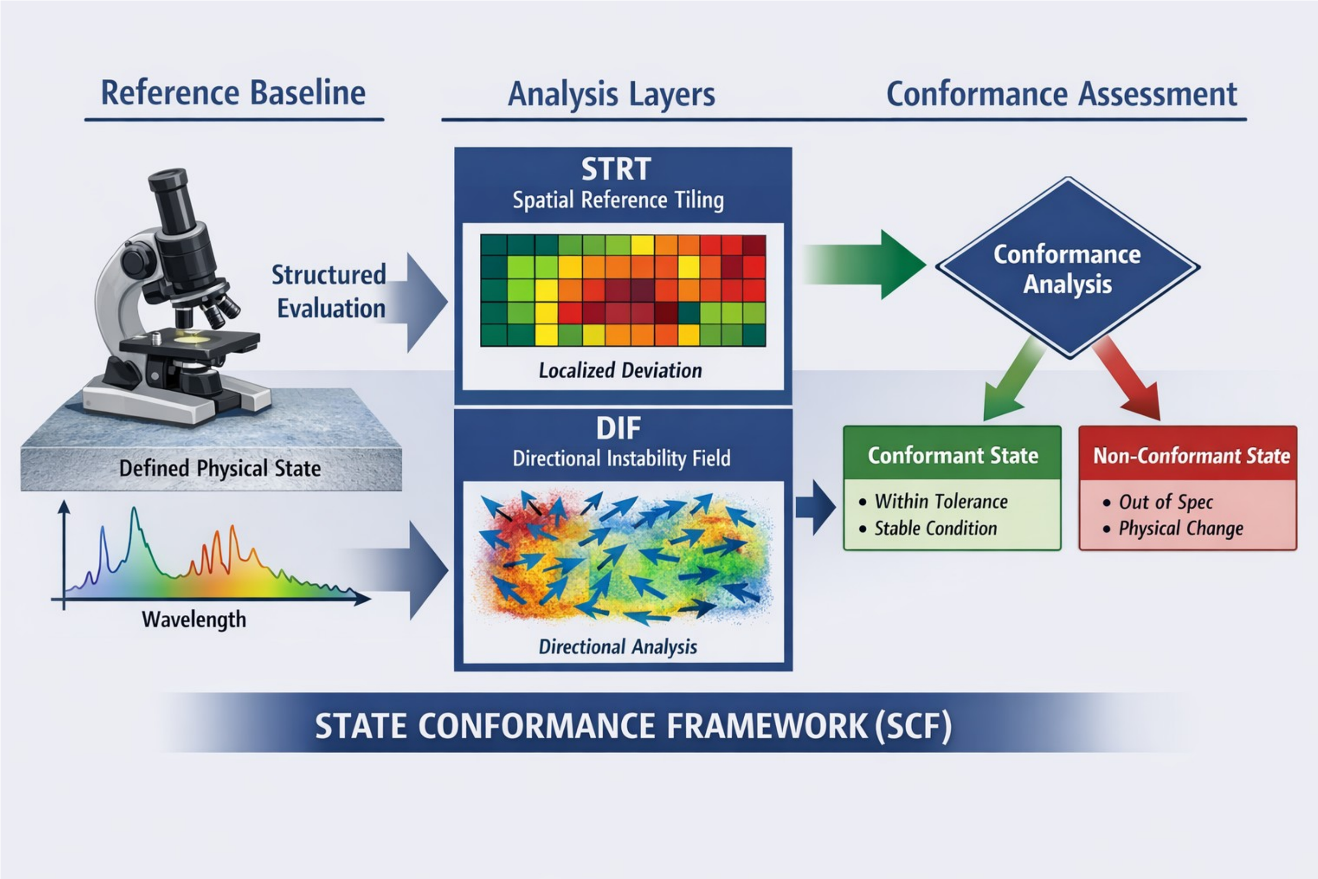

Figure 3. Schematic representation of the State Conformance Framework (SCF). A defined reference state anchors spatial tiling (STRT), directional coherence assessment (DIF), spectral redistribution analysis (SLE), and longitudinal drift evaluation (DAI), producing deterministic structural and energetic conformance validation.

2.2.1 Phase Topology in Thin-Film Deposition

Thin-film deposition events provide a physically grounded example of region-dependent phase behavior within the State Conformance framework. Figure 2 presents a raw prototype frame captured under controlled illumination using the current Phocoustic imaging stack. The frame illustrates a ring-like accumulation boundary with distributed interior perturbation relative to the surrounding exterior region.

Why Thin-Film Deposition Serves as a Conformance Proxy

Thin-film “coffee-ring” deposition provides a controlled physical analog for structured state deviation. The phenomenon is governed by evaporation-driven radial transport and edge accumulation dynamics, producing a predictable multi-regime topology consisting of stable exterior baseline, concentrated boundary manifold, and distributed interior perturbation. Because the underlying transport physics are well characterized, the resulting spatial configuration provides a deterministic test case for evaluating whether a measurement architecture can distinguish structured phase regimes, quantify regional drift contrast, and track longitudinal instability accumulation over time. The coffee-ring topology therefore serves as a physically grounded proxy for broader material redistribution and thin-film conformance phenomena observed in industrial surface processes.

Figure 4. *Raw frame acquired from the Phocoustic prototype under controlled darkfield illumination. A ring-like boundary region and distributed interior perturbation are visible relative to the exterior baseline. No artificial enhancement beyond standard acquisition normalization has been applied.*

Within this frame, three spatial regimes are distinguishable:

- **Exterior Region —** Statistically stable gradient distribution and low directional coherence. Drift measurements remain within baseline tolerance bounds.

- **Boundary Ring** — A connected manifold exhibiting elevated gradient magnitude and directional alignment.
- **Interior Region** — Distributed thin-film haze representing lower-contrast but statistically consistent deviation relative to the exterior.

These distinctions are not defined solely by pixel intensity, but by measurable differences in directional instability (DIF), spatial tiling structure (STRT), distributed drift magnitude (PADR_dist), and persistence behavior.

To clarify the structural interpretation of these regimes, a schematic abstraction is shown in Figure 3.

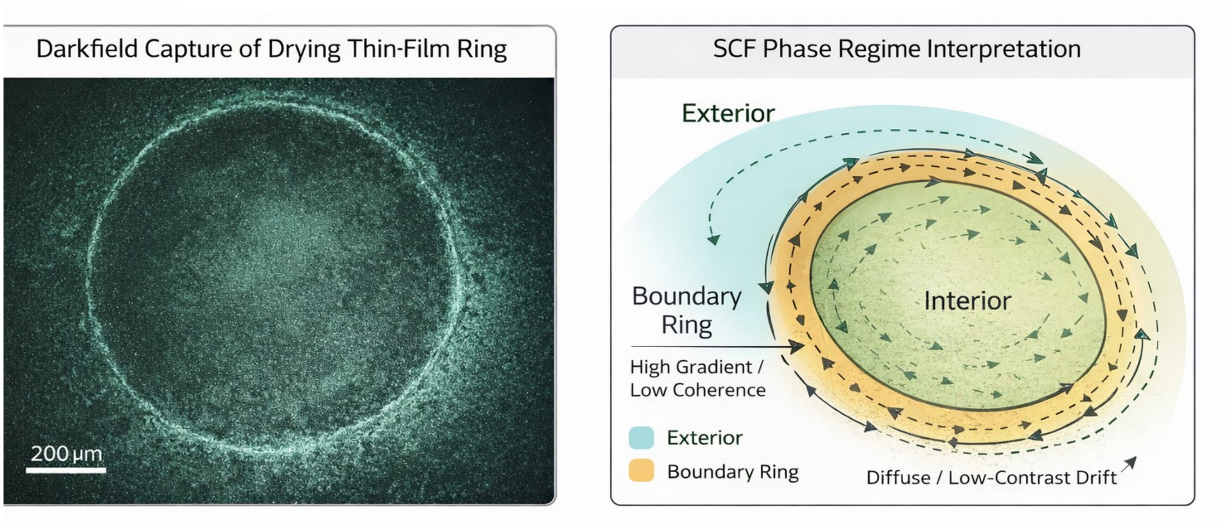

Figure 5 — Phase Regime Topology in Thin-Film Deposition.
Schematic abstraction corresponding to the empirical frame in Figure 5. The Exterior Region represents baseline phase stability. The Boundary Ring exhibits localized phase concentration characterized by elevated directional coherence (DIF) and connected structure (STRT). The Interior Region exhibits distributed phase perturbation associated with thin-film redistribution.

Exterior Region — Baseline Phase Stability

The exterior region represents the nominal conformant state. Gradient orientations are statistically isotropic, directional coherence remains low, and drift measurements exhibit minimal persistence. In this region:

- Directional coherence (DIF) is low to moderate and lacks dominant alignment.
- Connected component concentration (STRT) is minimal.
- Distributed drift magnitude (PADR_dist) remains within baseline bounds.

This region establishes the reference phase field against which perturbations are evaluated.

Boundary Ring — Localized Phase Concentration

At the deposition boundary, spatial gradients increase sharply and directional alignment becomes structured. Drift vectors tend to align tangentially or radially along the ring manifold, producing elevated directional coherence and connected component continuity.

In this region:

- DIF coherence increases significantly.
- STRT connected component ratio rises due to band continuity.
- Gradient magnitude is concentrated along a narrow manifold.

This constitutes a phase-concentrated structure — not merely high amplitude variation, but spatially organized phase alignment.

Interior Region — Distributed Phase Perturbation

Inside the boundary ring, the system often exhibits distributed thin-film haze. Unlike the boundary band, this region does not produce strong localized edges; instead, it manifests as a statistically consistent deviation across a broader area.

In this region:

- PADR_dist may increase relative to the exterior baseline.
- DIF coherence remains moderate or isotropic.
- STRT does not exhibit strong localized connected structures.
- Drift persistence across frames may increase.

This regime represents distributed phase shift rather than concentrated phase coherence.

Quantitative Interior–Exterior Phase Contrast

A useful diagnostic measure for thin-film haze is the difference between interior and exterior drift statistics:

$$\Delta_{\text{in-out}} = \mu(\text{drift} \mid \text{interior}) - \mu(\text{drift} \mid \text{exterior})$$

To normalize against background variability:

$$R_{\text{in-out}} = \frac{\Delta_{\text{in-out}}}{\sigma(\text{exterior}) + \epsilon}$$

These measures quantify whether the interior region exhibits statistically meaningful phase deviation relative to baseline.

Phase Regimes and State Conformance

The coffee-ring topology demonstrates that phase is not a binary anomaly indicator but a structured spatial regime. Within the State Conformance framework:

- The exterior region reflects stable phase alignment.
- The boundary ring reflects concentrated phase coherence.
- The interior region reflects distributed phase perturbation.
- Temporal persistence (LDE, DAI_1, DAI_2) determines whether such perturbations stabilize, dissipate, or accelerate.

State Conformance therefore evaluates phase topology across space and time, distinguishing structured deposition dynamics from random fluctuation or transient noise without presupposing direct process actuation.

Figure 6. Raw frame acquired from the Phocoustic prototype under controlled darkfield illumination. A ring-like boundary manifold and distributed interior redistribution are visible relative to the surrounding conformant exterior region. No artificial enhancement beyond acquisition normalization has been applied.

Within this frame, three spatial regimes are identifiable based on structured drift behavior:

• Exterior Region — Conformant Phase Field

The exterior region represents a validated conformant phase condition. Gradient orientations are predominantly isotropic, directional coherence remains low, and drift persistence is minimal.

In this regime:

- Directional coherence (DIF) lacks dominant alignment.
- STRT activation remains sparse and unclustered.
- Structured drift magnitude (PADR) remains within admissible tolerance bounds.

This region serves as a reference phase field within the SCF measurement architecture.

• Boundary Ring — Concentrated Phase Manifold

At the deposition boundary, spatial gradients increase sharply and directional alignment becomes organized. Drift vectors exhibit coherent radial or tangential alignment along the ring manifold, producing elevated directional reinforcement and spatial continuity.

In this regime:

- DIF coherence increases substantially.
- STRT connected activation rises due to band continuity.
- Gradient magnitude concentrates along a narrow, connected manifold.

This structure represents phase concentration rather than isolated amplitude variation — a spatially organized regime characterized by directional reinforcement.

• Interior Region — Distributed Phase Redistribution

Inside the boundary manifold, distributed thin-film haze often appears. Unlike the boundary band, this region does not exhibit sharp localized gradients. Instead, it manifests as spatially distributed redistribution of scattering energy across a broader domain.

In this regime:

- Distributed drift magnitude (PADR) increases relative to the exterior conformant region.
- DIF coherence remains moderate or near-isotropic.
- STRT activation is distributed rather than concentrated.
- Drift persistence across frames may increase depending on film stability.

This regime reflects distributed phase redistribution rather than concentrated phase coherence.

Quantitative Interior–Exterior Phase Contrast

A deterministic contrast measure between interior and exterior regimes may be defined as:

$$\Delta_{\text{in-out}} = \mu(\text{drift} \mid \text{interior}) - \mu(\text{drift} \mid \text{exterior})$$

To normalize against background variability:

Rin-out=Δin-outσ(exterior)+ϵR_{\text{in-out}} = \frac{\Delta_{\text{in-out}}}{\sigma(\text{exterior}) + \epsilon}Rin-out=σ(exterior)+ϵΔin-out

These measures quantify relative phase displacement between distributed redistribution and conformant regions without invoking probabilistic inference.

Phase Regimes Within the SCF–SCE Architecture

The coffee-ring topology demonstrates that phase behavior is structured and regime-dependent rather than binary. Within the State Conformance Framework (SCF):

- The exterior region reflects admissible phase alignment.
- The boundary ring reflects concentrated directional reinforcement.
- The interior region reflects distributed redistribution of scattering energy.

SCF deterministically measures spatial, directional, and magnitude displacement across these regimes. The State Convergence Engine (SCE) then evaluates longitudinal trajectory—determining whether distributed redistribution stabilizes within admissible bounds, dissipates toward a validated reference state, or accumulates toward instability.

State Conformance therefore evaluates phase topology across space and time, distinguishing structured deposition dynamics from transient fluctuation without reliance on anomaly classification or probabilistic modeling.

2.2 Component Definitions and Roles

The State Conformance Framework (SCF) is composed of deterministic measurement components that collectively define the structured conformance vector v(t)\mathbf{v}(t)v(t). Each component captures a distinct physical dimension of surface behavior: spatial localization, directional structure, integrated drift magnitude, temporal evolution, amplitude persistence, and spectral redistribution. Together, these components form a geometrically interpretable state representation that serves as the input to convergence evaluation under the State Convergence Engine (SCE).

STRT — Spatial Topology Response Tracking

STRT establishes the spatial substrate of the framework. It partitions the observed surface into structured tiles relative to a validated reference condition and evaluates localized deviation within each partition.

STRT produces:

- Activated tile maps
- Connected-component structures
- Boundary localization metrics
- Spatial distribution profiles
- Region-specific deviation intensity

Functionally, STRT answers:

Where does measurable deviation occur within the surface domain?

STRT transforms deviation from an aggregate quantity into a geographically accountable structure. Without STRT, drift can be measured but not spatially localized.

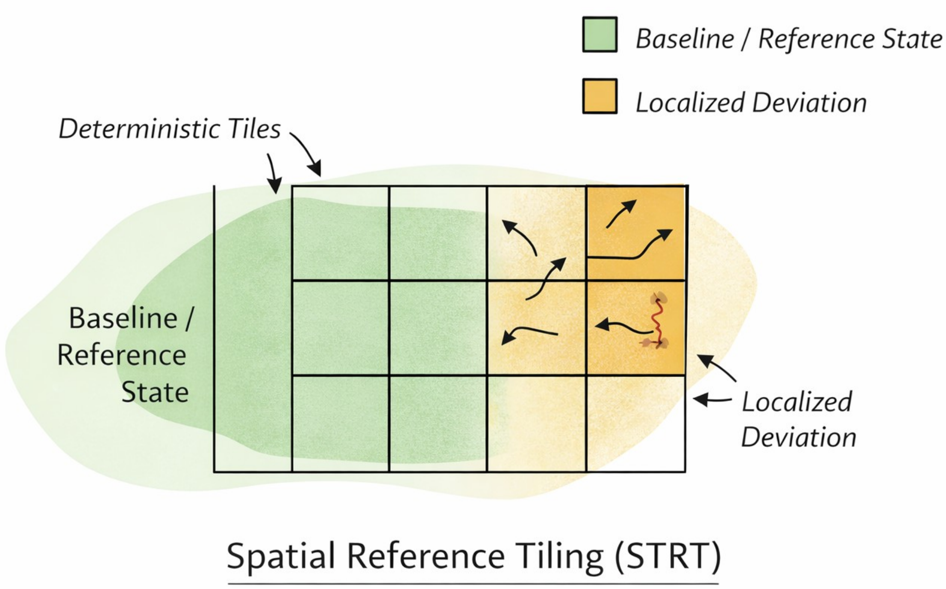

Figure 7. Spatial Topology Response Tracking (STRT): Structured partitioning of the observed surface into deterministic tiles enabling localized deviation measurement relative to validated reference states.

DIF — Directional Integrity Field

DIF characterizes the internal organization of drift within STRT-activated regions. It evaluates the coherence and reinforcement of directional gradients.

DIF measures:

- Drift vector alignment
- Orientation stability
- Gradient reinforcement versus isotropy
- Spatial coherence of directional fields

Physically meaningful state transitions—such as deposition boundaries, stress propagation, or transport-driven redistribution—exhibit coherent directional structure. Transient fluctuation does not.

DIF answers:

Is the observed deviation structurally organized in a manner consistent with physical process behavior?

Directional coherence functions as a signature of structural legitimacy rather than random fluctuation.

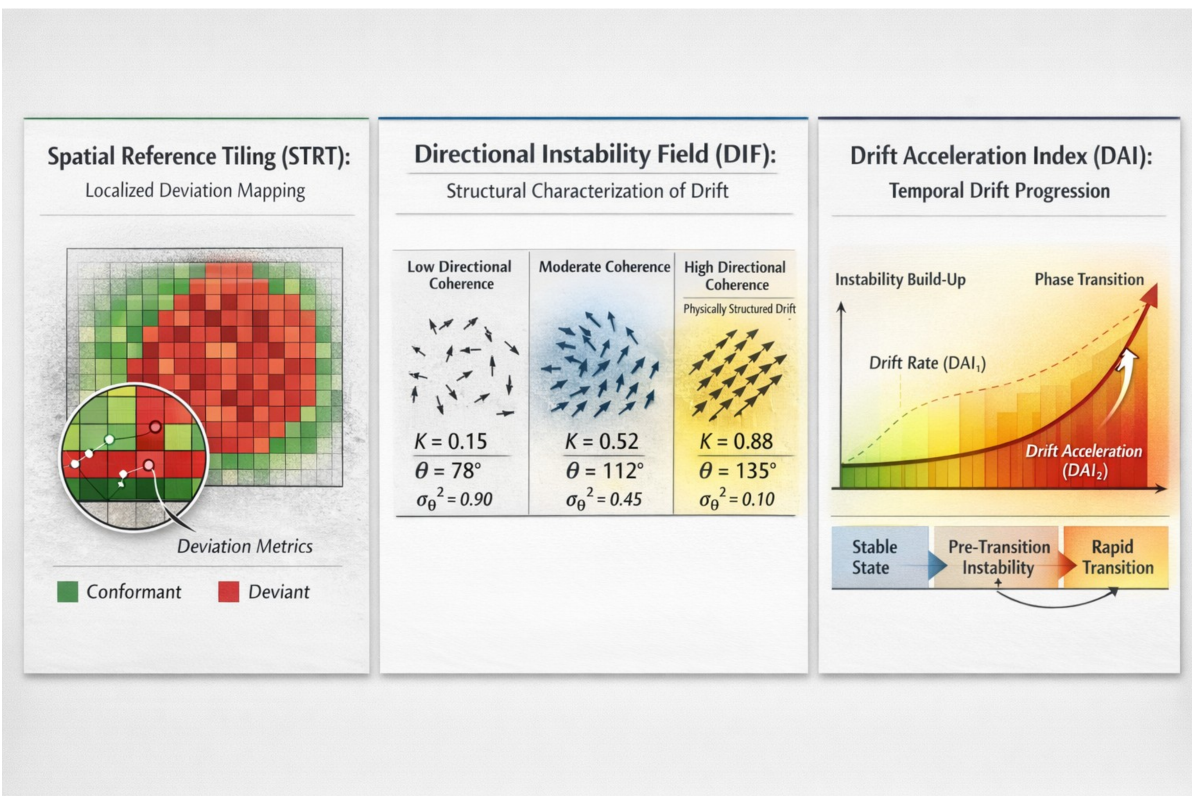

Figure 7a Directional Integrity Field (DIF): Vector-field representation illustrating coherent gradient alignment within activated spatial regions.

SDF — Structured Drift Flux

SDF integrates directional drift magnitude across the spatial domain. Whereas STRT localizes and DIF characterizes structure, SDF quantifies accumulated drift behavior at the domain level.

SDF provides:

- Domain-integrated drift magnitude
- Flux accumulation metrics
- Spatially weighted drift intensity

SDF answers:

How much structured drift is present across the system as a whole?

This component bridges localized structure and temporal evolution, serving as a precursor metric for longitudinal analysis.

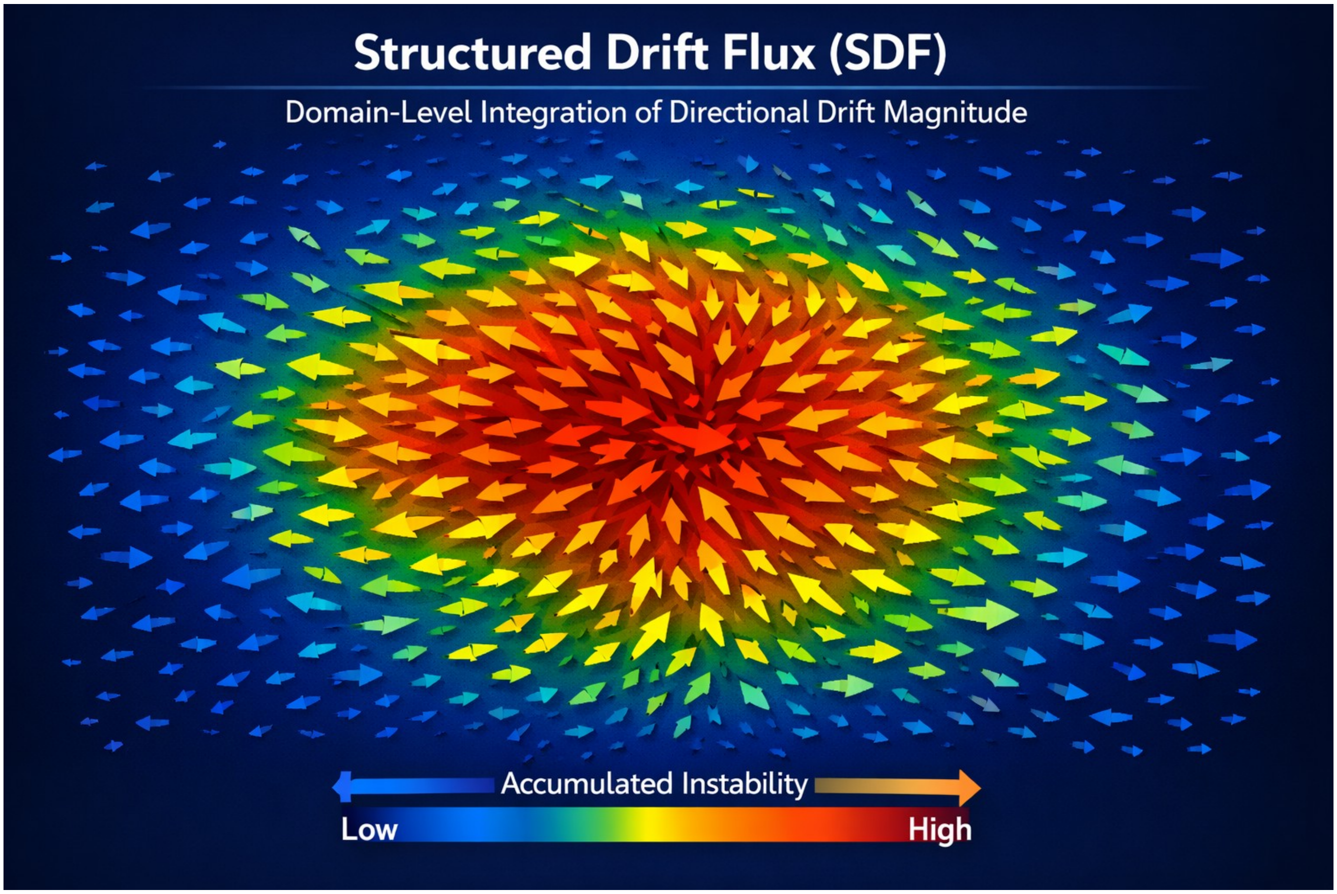

Figure 8. Structured Drift Flux (SDF): Domain-level integration of directional drift magnitude illustrating accumulated instability across the surface.

DAI — Drift Acceleration Index

DAI extends SCF into the temporal domain by evaluating first- and second-order derivatives of structured drift metrics.

DAI1(t)=ddt(Structured Drift)DAI_1(t) = \frac{d}{dt}(\text{Structured Drift})DAI1(t)=dtd (Structured Drift) DAI2(t)=d2dt2(Structured Drift)DAI_2(t) = \frac{d^2}{dt^2}(\text{Structured Drift})DAI2(t)=dt2d2(Structured Drift)

Where:

- DAI1DAI_1DAI1 represents instability growth rate
- DAI2DAI_2DAI2 represents instability acceleration

DAI determines whether deviation:

- Is emerging
- Is stabilizing
- Is accelerating
- Has plateaued

Sustained positive acceleration indicates accumulating structural displacement that may precede visible macroscopic change.

DAI answers:

Is the system drifting, stabilizing, or accelerating within conformance space?

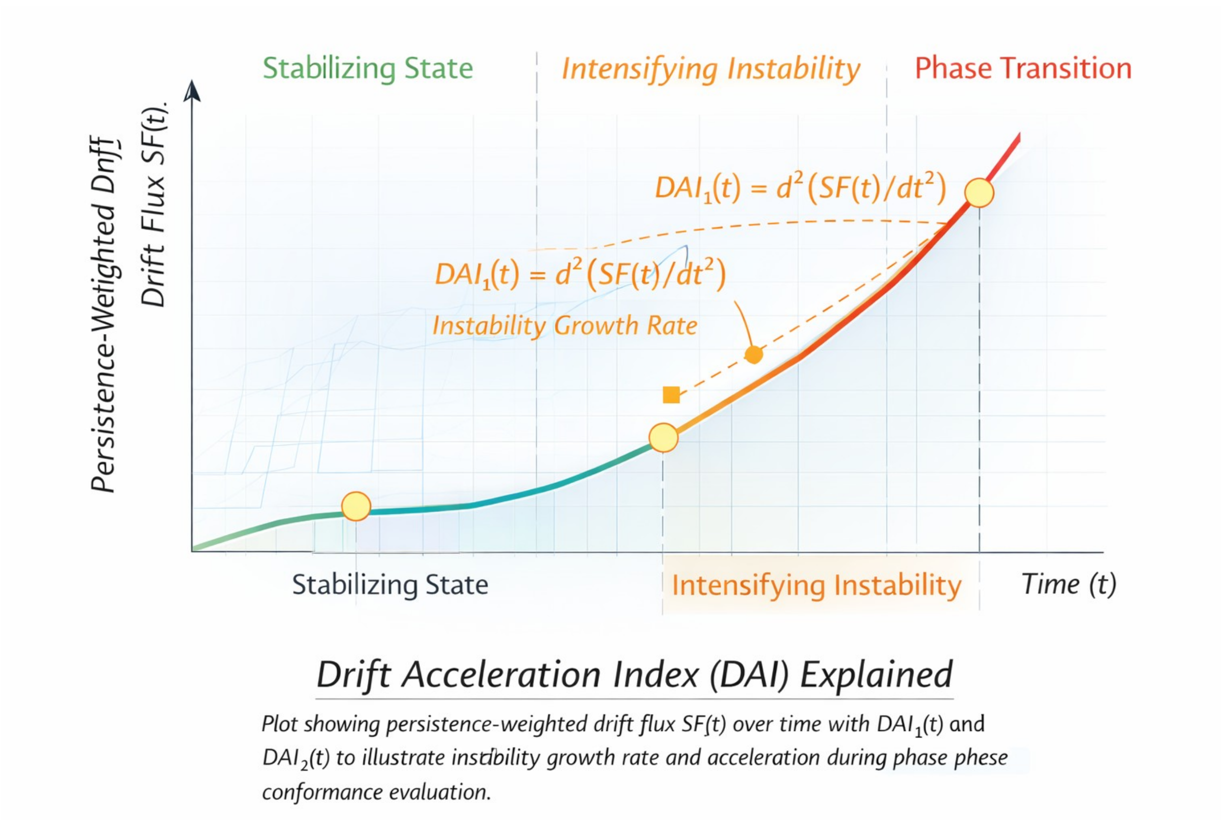

Figure 9. Drift Acceleration Index (DAI): Conceptual longitudinal drift trajectory showing growth rate (DAI_1) and acceleration (DAI_2) within structured conformance space.

PADR — Physics-Anchored Drift Regulation

PADR regulates drift magnitude through persistence validation and physical admissibility constraints. It ensures that only multi-frame, directionally and temporally consistent drift signatures contribute to the conformance vector.

PADR enforces:

- Multi-frame stability
- Persistence filtering
- Suppression of transient fluctuation
- Deterministic amplitude quantification

PADR provides:

- Drift amplitude metrics
- Persistence-weighted magnitude
- Rejection of isolated artifacts

PADR answers:

How strong is the deviation, and does it persist in a physically consistent manner?

It anchors SCF in measurable amplitude rather than isolated excursions.

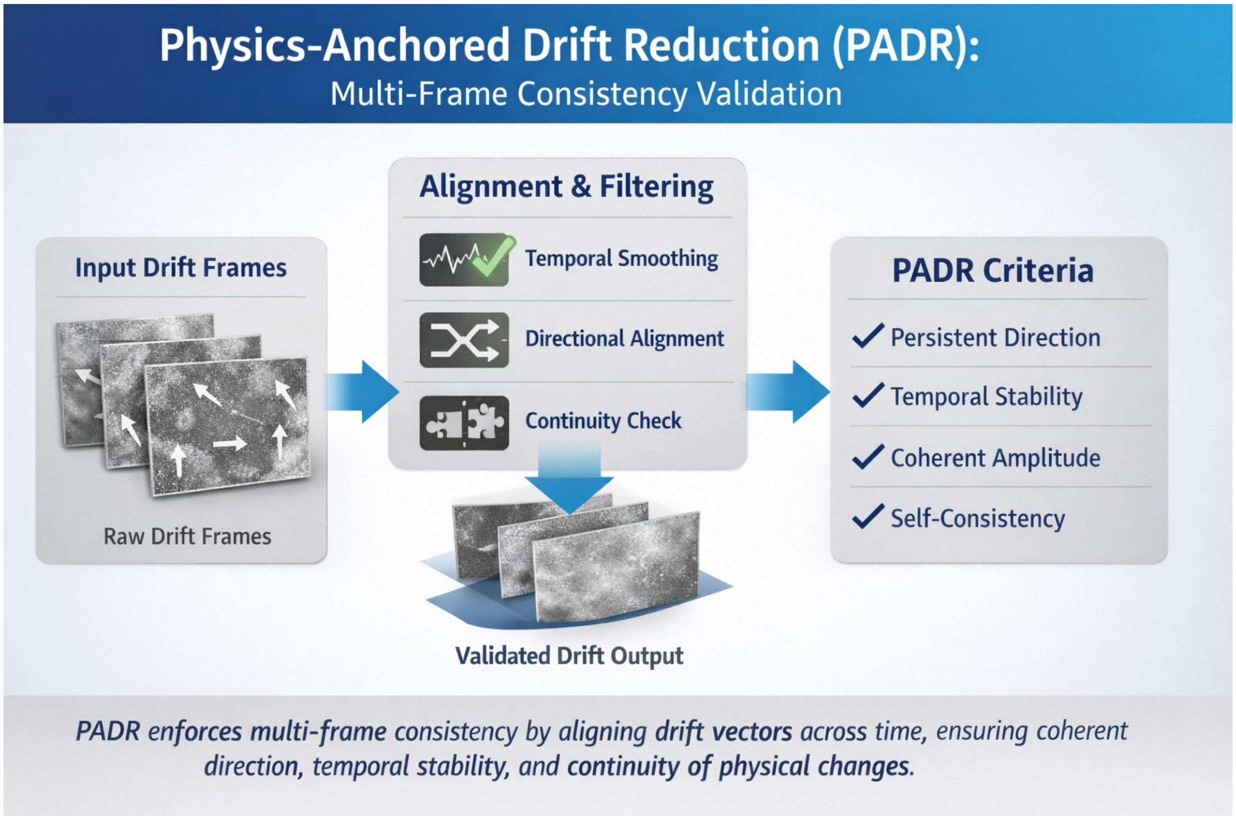

Figure 10. Physics-Anchored Drift Regulation (PADR): Multi-frame persistence filtering ensuring only lineage-consistent drift signatures contribute to structured conformance evaluation.

SLE — Spectral Loss Energy

SLE quantifies redistribution or attenuation of spectral energy relative to validated reference states.

In thin films and scattering surfaces, structural changes often alter:

- Backscatter intensity
- High-frequency spectral content
- Micro-texture reflectivity
- Diffuse versus specular balance

SLE functions as a proxy for:

- Material absorption shifts
- Surface haze formation
- Micro-layer deposition

- Subtle refractive index variation

SLE answers:

Has the energetic signature of the surface shifted in a manner consistent with physical state change?

Unlike directional metrics such as DIF, SLE captures energetic redistribution independent of strong vector coherence. This makes it particularly valuable in thin-film and haze-dominant regimes where directional structure may be weak but spectral attenuation remains measurable.

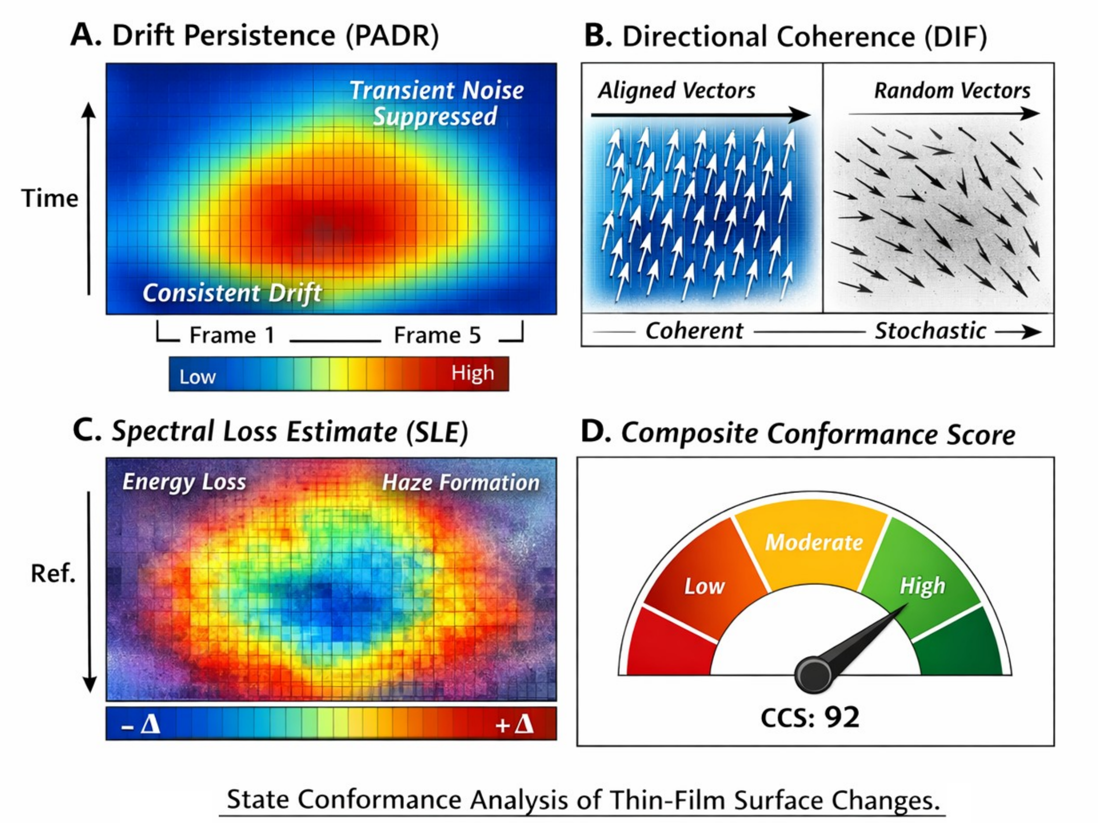

Figure 11. Spectral Loss Energy (SLE) Map: Spatially resolved representation of spectral redistribution relative to validated reference conditions, highlighting regions of energetic attenuation consistent with thin-film perturbation.

Integrated Role Within SCF

Collectively, STRT, DIF, SDF, DAI, PADR, and SLE define the structured conformance vector v(t)\mathbf{v}(t)v(t). SCF measures spatial position within conformance space; SCE evaluates trajectory and stabilization relative to validated reference states.

This layered architecture ensures that deviation is:

- Spatially accountable
- Directionally structured
- Amplitude-regulated
- Spectrally validated
- Temporally resolved

The result is a deterministic, physically grounded measurement stack suitable for thin-film validation, wafer inspection, coating verification, and precision surface process control.

2.3 Interpretation of v(t)\mathbf{v}(t)v(t) Under SCF

The output of the State Conformance Framework at time ttt is the structured conformance vector v(t)\mathbf{v}(t)v(t), not a single scalar indicator.

This vector represents the measured position of the surface within deterministic conformance space and is composed of coordinated components derived from:

- Spatial Activation Profile (STRT)
- Persistence-Weighted Drift Magnitude (PADR)
- Directional Coherence Field (DIF)
- Structured Drift Flux (SDF)
- Drift Acceleration Index (DAI)
- Spectral Loss Energy (SLE)

Each component contributes an distinct measurement dimension of physical interpretation—spatial distribution, amplitude persistence, directional organization, accumulated drift, temporal evolution, and energetic redistribution.

Operationally, the structured conformance vector v(t)\mathbf{v}(t)v(t) may be represented as:

- A multi-dimensional conformance dashboard
- A tolerance-bound compliance evaluation
- A graded deviation profile across defined conformance axes
- A deterministic admissibility assessment under predefined envelopes

Importantly, SCF does not determine convergence or final admissibility. It computes the measurement geometry required for such evaluation. Convergence relative to validated reference states is performed by the State Convergence Engine (SCE), which interprets trajectory and proximity within defined conformance envelopes.

The structured conformance vector v(t)\mathbf{v}(t)v(t), as produced by SCF, supports:

- Deterministic compliance verification
- Quantitative deviation characterization
- Early-stage instability detection via acceleration metrics
- Post-process stabilization confirmation

Null displacement is itself a meaningful measurement condition. When:

- STRT activation remains sparse,
- DIF coherence lacks directional reinforcement,
- SDF remains minimal,
- DAI indicates stable or decelerating drift,
- PADR magnitude remains within admissible bounds, and
- SLE shows no measurable spectral redistribution,

the system deterministically verifies that the surface resides within the validated reference envelope.

Thus, SCF does not infer abnormality; it measures structured state position. SCE subsequently evaluates whether that position is converging toward, diverging from, or stabilizing within admissible reference conditions.

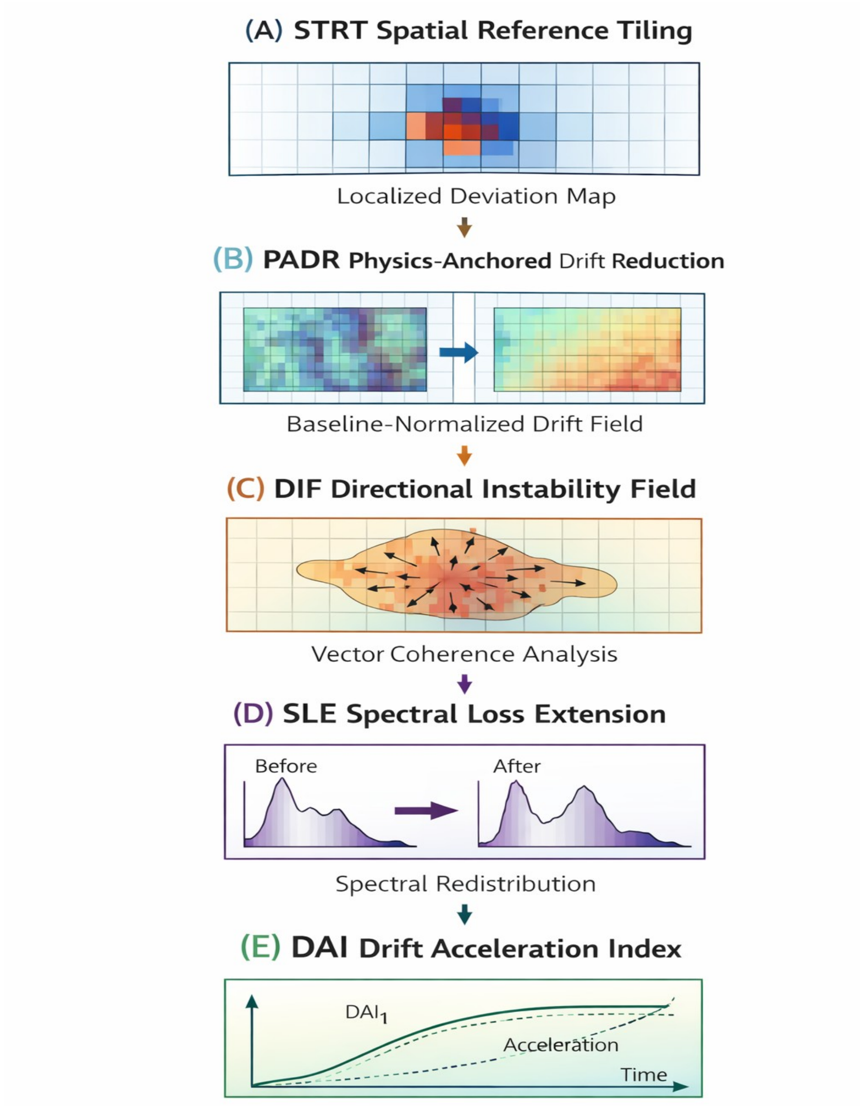

Figure 12 — Structured Conformance Vector v(t) Within the State Conformance Framework (SCF).

Stacked visualization of the deterministic measurement pipeline that produces the structured conformance vector **v(t)** at time *t*. Rather than a scalar anomaly score, SCF outputs a multi-dimensional state position in conformance space derived from coordinated physical components:

(A) **STRT — Spatial Activation Profile:** Localized deviation mapping relative to a defined reference state.
(B) **PADR — Persistence-Weighted Drift Magnitude:** Baseline-normalized drift field filtered for temporal persistence and admissibility.

(C) **DIF — Directional Coherence Field:** Vector coherence analysis distinguishing structured instability from stochastic variation.
(D) **SLE — Spectral Loss Energy:** Quantification of energetic redistribution and texture attenuation across spectral domains.
(E) **DAI — Drift Acceleration Index:** First- and second-order temporal derivatives of structured drift capturing growth rate and instability acceleration.

Together, these components define the structured conformance vector:

v(t) = {STRT, PADR, DIF, SDF, SLE, DAI}

Each axis represents a distinct physical measurement dimension—spatial distribution, amplitude persistence, directional organization, accumulated flux, spectral redistribution, and temporal evolution. The vector specifies the surface's position within deterministic conformance space and may be operationally expressed as a graded deviation profile, tolerance-bound compliance evaluation, or multi-dimensional conformance dashboard.

Importantly, SCF computes the geometry of measurement; it does not determine admissibility. Convergence, divergence, or stabilization relative to validated reference envelopes is interpreted downstream by the State Convergence Engine (SCE), which evaluates trajectory and proximity within predefined conformance boundaries.

Null displacement constitutes a meaningful condition. When spatial activation remains sparse, directional reinforcement is absent, accumulated drift flux is minimal, acceleration is stable or decelerating, persistence-weighted magnitude remains bounded, and no spectral redistribution is detected, the system deterministically verifies that the surface resides within the validated reference envelope.

SCF therefore measures structured state position. SCE subsequently evaluates whether that position is converging toward, diverging from, or stabilizing within admissible conformance conditions.

2.4 Deterministic Nature of the Framework

The State Conformance Framework is deterministic by construction.

Determinism arises from three architectural principles:

1. **Validated Reference States**
   Reference states are intentionally defined, captured, and stored within a Reference State Library (RSL). They are not statistically inferred but physically established under controlled acquisition conditions.

2. **Measurable Physical Quantities**
   All SCF components correspond to physically measurable constructs: spatial activation (STRT), directional coherence (DIF), accumulated drift flux (SDF), temporal derivatives (DAI), persistence-weighted amplitude (PADR), and spectral redistribution (SLE). Each metric is computed through explicit mathematical operations applied to observed scattering fields.
3. **Non-Probabilistic Aggregation**
   The conformance vector v(t)\mathbf{v}(t)v(t) is generated through deterministic aggregation of measurable quantities. No learned defect classes, training distributions, or probabilistic classifiers are required for operation.

Because each component is independently interpretable and physically grounded, thresholds may be calibrated against known material conditions and validated through repeatable measurement procedures. This structure aligns directly with established paradigms in industrial metrology, quality assurance, and process control, where traceability, repeatability, and calibration stability are mandatory.

SCF therefore operates as a measurement architecture rather than an inference engine.

Convergence evaluation relative to validated reference states is subsequently performed by the State Convergence Engine (SCE), preserving architectural separation between measurement and trajectory assessment.

2.5 Conceptual Significance

The State Conformance architecture formalizes a shift in inspection philosophy: from probabilistic anomaly detection to deterministic state verification within structured conformance space.

Conventional systems typically frame the problem as:

> “Is this unusual relative to historical data?”

The SCF–SCE architecture reframes the question as:

> “Does the observed surface reside within an admissible reference state, and if not, how does it diverge in spatial, directional, temporal, and energetic dimensions?”

This reframing is conceptually significant because it replaces statistical abnormality inference with geometrically interpretable state positioning.

By integrating:

- **STRT —** spatial localization
- **DIF —** directional structure
- **SDF —** accumulated drift flux

- **DAI** — temporal evolution
- **PADR —** persistence-weighted magnitude
- **SLE —** spectral redistribution

the framework transforms deviation into structured state descriptors that are:

- Spatially localized
- Directionally characterized
- Temporally resolved
- Amplitude-regulated
- Energetically validated

The result is an architecture capable of verifying conformance, quantifying divergence, and evaluating stabilization trajectories without reliance on probabilistic anomaly scoring.

In industrial thin-film validation, wafer processing, coating verification, and structured surface monitoring, this shift enables deterministic auditability, calibration stability, and physically interpretable process governance.

Section 6 formalizes deterministic convergence, proximity evaluation, and admissibility logic under the State Convergence Engine (SCE), which operates on the structured conformance vector v(t)\mathbf{v}(t)v(t).

3. Operationalization of the State Conformance Framework

Section 2 defined the State Conformance Framework (SCF) as a deterministic measurement architecture that computes the structured conformance vector v(t)\mathbf{v}(t)v(t). Section 3 formalizes how these component measurements are constructed, integrated, and stabilized in practice.

The purpose of this section is not to introduce new evaluative logic, but to describe the computational mechanics by which spatial, directional, temporal, magnitude, and spectral quantities are extracted from observed scattering fields and assembled into conformance space.

Within the SCF–SCE hierarchy:

- **SCF** computes measurable state position through structured drift geometry.
- **SCE** evaluates proximity, trajectory, and admissibility relative to validated reference states.

Section 3 therefore focuses exclusively on the SCF layer: how drift fields are derived, how spatial partitions are enforced, how directional structure is quantified, how accumulated flux is integrated, and how temporal derivatives are computed under deterministic constraints.

The operational pipeline proceeds through five sequential measurement domains:

1. Spatial partitioning and localized activation (STRT)
2. Directional field estimation and coherence quantification (DIF)
3. Accumulated structured drift integration (SDF)
4. Temporal derivative modeling (DAI)
5. Spectral redistribution measurement (SLE)

Each domain contributes an independently computed dimension to the structured conformance vector v(t)\mathbf{v}(t)v(t). Together, these components define the measurable geometry of surface state at time ttt.

Importantly, Section 3 does not evaluate whether a state is admissible or convergent. It defines how measurable conformance coordinates are constructed. Convergence analysis and multi-reference evaluation are formalized separately under the State Convergence Engine (Section 6).

By separating measurement construction (SCF) from convergence logic (SCE), the architecture maintains deterministic clarity, modular extensibility, and industrial traceability.

3.1 Drift Field Construction

Let the observed optical frame at time ttt be defined as:

I(x,y,t)I(x,y,t)I(x,y,t)

where:

- x,yx, yx,y denote spatial coordinates in the image domain,
- ttt denotes discrete acquisition time (frame index),
- III represents the measured intensity or multi-spectral signal response under controlled illumination conditions.

The drift field is defined as the deterministic transformation of the observed signal relative to one or more validated reference states contained within the Reference State Library (RSL).

Formally:

D(x,y,t)=V(I(x,y,t),Ri)D(x,y,t) = \mathcal{V}\big(I(x,y,t), R_i\big)D(x,y,t)=V(I(x,y,t),Ri)

where:

- D(x,y,t)D(x,y,t)D(x,y,t) denotes the structured drift magnitude at spatial coordinate (x,y)(x,y)(x,y),
- RiR_iRi denotes a validated reference state,
- V(·)\mathcal{V}(\cdot)V(·) denotes the VAAD operator (Variance-Anchored Absolute Drift transformation).

The VAAD operator is a deterministic mapping that converts measured signal intensity into a structured drift representation by quantifying deviation relative to a reference scattering field. This transformation may incorporate spatial normalization, variance anchoring, and persistence conditioning to ensure calibration stability and repeatability.

Importantly, the drift field D(x,y,t)D(x,y,t)D(x,y,t) does not represent probabilistic abnormality. It represents measurable displacement within conformance space. The drift field serves as the foundational signal from which higher-order SCF components are derived, including spatial activation (STRT), directional coherence (DIF), structured drift flux (SDF), and temporal acceleration (DAI).

By separating raw signal acquisition I(x,y,t)I(x,y,t)I(x,y,t) from deterministic drift transformation D(x,y,t)D(x,y,t)D(x,y,t), the framework ensures that subsequent conformance metrics are grounded in explicitly defined reference geometry rather than learned statistical distributions.

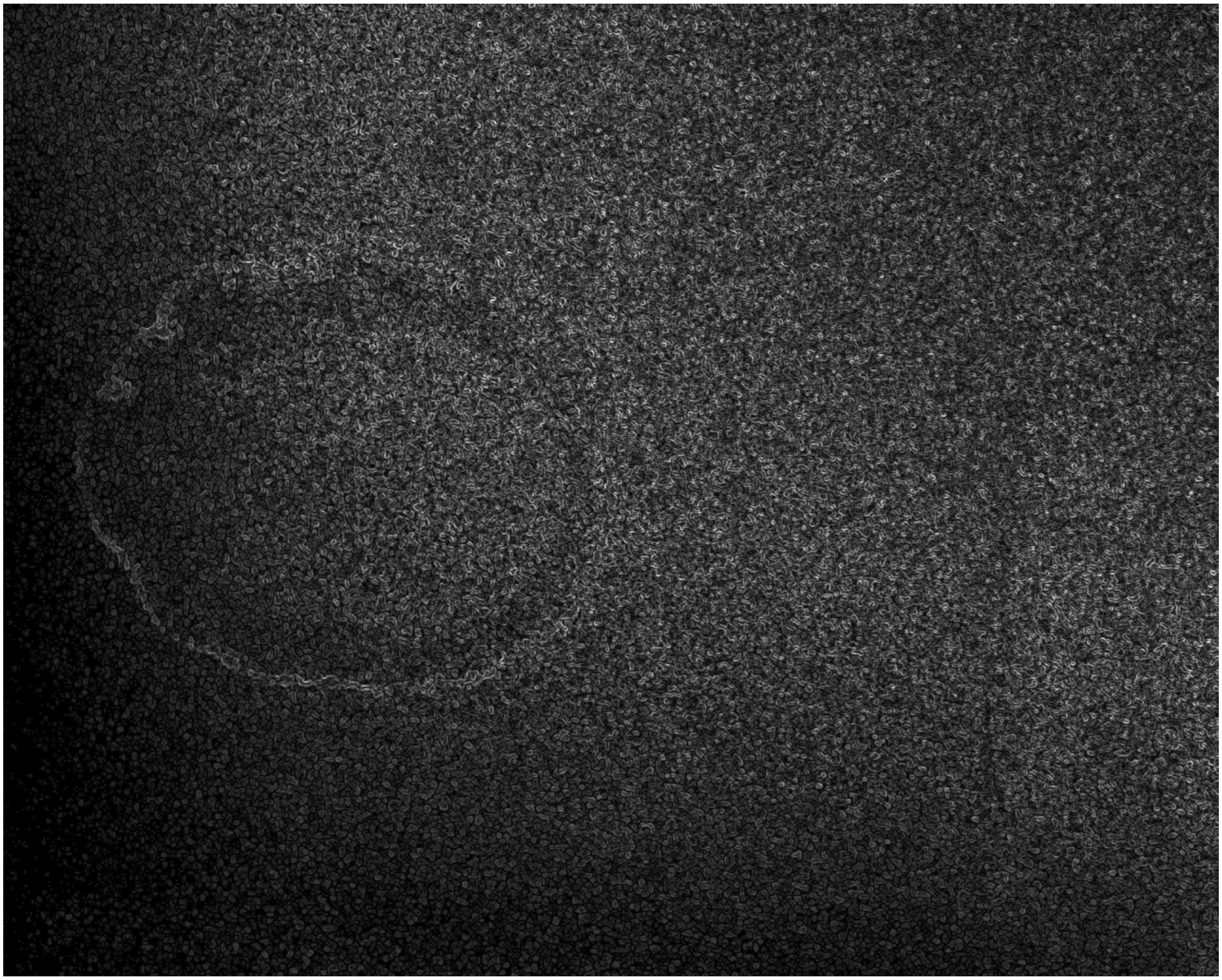

Figure 13 — Drift Field D(x,y,t) Computed drift field showing spatial deviation relative to baseline reference. Circular structure becomes topologically amplified under drift transformation.

3.1.1 Reference-Relative Drift

Let a validated reference frame from the Reference State Library (RSL) be defined as:

IRi(x,y)I_{R_i}(x,y)IRi(x,y)

where RiR_iRi denotes a validated reference state captured under controlled and conformant acquisition conditions.

The primary signal displacement relative to this reference is defined as:

ΔIi(x,y,t)=I(x,y,t)−IRi(x,y)\Delta I_i(x,y,t) = I(x,y,t) - I_{R_i}(x,y)ΔIi(x,y,t)=I(x,y,t)−IRi(x,y)

This quantity represents raw intensity displacement at spatial coordinate (x,y)(x,y)(x,y) and time ttt relative to reference state RiR_iRi.

However, direct subtraction is not sufficient for stable drift estimation. Global illumination variation, sensor gain shifts, low-frequency background gradients, and acquisition noise must be accounted for to preserve physical interpretability and calibration consistency.

The VAAD transformation therefore incorporates deterministic conditioning stages, including:

1. Local spatial normalization to remove global intensity bias
2. Multi-scale gradient evaluation to capture structured drift geometry
3. Variance anchoring to suppress background heterogeneity
4. Drift persistence weighting across frames
5. Physics-Anchored Drift Regulation (PADR) to suppress transient fluctuation

The structured drift field is therefore computed as:

D(x,y,t;Ri)=F(ΔIi(x,y,t), ∇I(x,y,t), σlocal(x,y,t), P(x,y,t))D(x,y,t; R_i) = \mathcal{F}\Big(\Delta I_i(x,y,t),\, \nabla I(x,y,t),\, \sigma_{\text{local}}(x,y,t),\, P(x,y,t) \Big)D(x,y,t;Ri)=F(ΔIi (x,y,t),∇I(x,y,t),σlocal(x,y,t),P(x,y,t))

where:

- F(·)\mathcal{F}(\cdot)F(·) is a deterministic operator,
- ∇I\nabla I∇I denotes local gradient structure,
- σlocal\sigma_{\text{local}}σlocal denotes local variance statistics,
- P(x,y,t)P(x,y,t)P(x,y,t) denotes temporal persistence weighting.

The operator F\mathcal{F}F is explicitly defined and does not rely on learned parameters or probabilistic classification. Its purpose is to convert raw signal displacement into a structured drift representation consistent with physical scattering behavior.

By incorporating normalization, gradient structure, and persistence regulation, the resulting drift field D(x,y,t;Ri)D(x,y,t; R_i)D(x,y,t;Ri) reflects measurable conformance displacement rather than transient signal fluctuation.

This reference-relative drift field forms the foundational input to spatial activation (STRT), directional coherence estimation (DIF), structured drift flux integration (SDF), and temporal acceleration modeling (DAI) within the State Conformance Framework.

3.1.2 Physical Interpretation of the Drift Field

The structured drift field D(x,y,t;Ri)D(x,y,t; R_i)D(x,y,t;Ri) represents measurable redistribution of optical scattering behavior relative to a validated reference state RiR_iRi.

Physically, the drift field captures spatially resolved changes including:

- Redistribution of scattering energy
- Micro-texture reflectivity variation
- Thin-film deposition or removal signatures
- Surface haze formation
- Emergence of boundary-layer gradients
- Localized structural perturbation

The magnitude of D(x,y,t;Ri)D(x,y,t; R_i)D(x,y,t;Ri) at a given coordinate reflects the extent to which the observed surface response diverges from the validated reference geometry under controlled illumination conditions.

Elevated drift magnitude indicates structured displacement within conformance space. Minimal drift magnitude indicates adherence to the reference state envelope.

Importantly, the drift field is not a probabilistic heatmap and does not represent inferred abnormality. It is a deterministic, physically interpretable measurement derived from reference-relative signal transformation. Each drift value corresponds to measurable intensity redistribution conditioned by normalization, gradient structure, and persistence weighting.

Thus, the drift field provides the foundational physical quantity from which higher-order SCF metrics —spatial activation (STRT), directional coherence (DIF), structured drift flux (SDF), and temporal acceleration (DAI)—are constructed.

In this sense, the drift field represents measurable state displacement rather than statistical anomaly scoring.

3.1.3 Drift Field as the Substrate of State Conformance

The structured drift field

D(x,y,t;Ri)D(x,y,t; R_i)D(x,y,t;Ri)

serves as the foundational measurement substrate of the State Conformance Framework (SCF).

All higher-level SCF components are derived from this reference-relative drift representation:

- **STRT** partitions D(x,y,t;Ri)D(x,y,t; R_i)D(x,y,t;Ri) into structured spatial tiles to localize measurable deviation.
- **DIF** evaluates directional coherence using gradients and vector fields derived from D(x,y,t;Ri)D(x,y,t; R_i)D(x,y,t;Ri).
- **SDF** integrates spatially resolved drift into accumulated flux measures across the domain.
- **DAI** computes temporal derivatives of structured drift quantities to assess growth or stabilization dynamics.
- **PADR** regulates drift magnitude through persistence weighting and physical continuity constraints.
- **SLE** evaluates spectral redistribution associated with spatial regions exhibiting drift displacement.

Thus, the drift field is the deterministic signal substrate from which the structured conformance vector v(t)\mathbf{v}(t)v(t) is constructed.

Importantly, the drift field belongs to the SCF measurement layer. The State Convergence Engine (SCE) does not operate directly on raw image data; it evaluates the position and trajectory of v(t)\mathbf{v}(t)v(t), which is ultimately derived from the structured drift field.

By anchoring all conformance metrics to a common reference-relative drift representation, the architecture maintains mathematical cohesion, traceability, and modular extensibility across spatial, directional, temporal, and spectral domains.

3.1.4 Drift Field Topology

The structured drift field

D(x,y,t;Ri)D(x,y,t; R_i)D(x,y,t;Ri)

is not solely a scalar magnitude distribution. Its spatial topology encodes diagnostic information regarding the geometry and organization of conformance displacement.

Beyond pointwise amplitude, the drift field contains measurable structural properties, including:

- Spatial gradient magnitude and orientation
- Connected-component continuity and area

- Boundary curvature and manifold structure
- Interior–exterior drift contrast
- Drift distribution entropy and dispersion

These properties describe how drift is organized across the domain rather than simply how large it is.

For example, in the thin-film deposition experiment described earlier:

- The boundary manifold exhibits elevated gradient magnitude and coherent spatial alignment.
- The interior region exhibits distributed, lower-amplitude drift with broader spatial spread.
- The exterior region remains within admissible conformance bounds relative to the validated reference state.

Such spatial heterogeneity is fundamental to state interpretation. A narrow, high-gradient band reflects concentrated structural reorganization, whereas diffuse interior displacement reflects distributed material redistribution. Regions exhibiting minimal gradient structure indicate conformance stability.

These topological characteristics provide the direct input to:

- **STRT**, which partitions and localizes structured drift regions, and
- **DIF**, which evaluates directional coherence within those localized regions.

Thus, drift topology forms the geometric bridge between raw reference-relative displacement and structured conformance metrics. It enables the framework to distinguish concentrated boundary phenomena, distributed film perturbation, and stable conformant regions within a unified deterministic representation.

3.1.5 Drift Field Stability and Admissibility Conditioning

The raw drift field D(x,y,t;Ri)D(x,y,t; R_i)D(x,y,t;Ri) is not directly propagated into higher-order conformance metrics. It must first satisfy deterministic persistence and continuity constraints to ensure physical admissibility.

Let

D~(x,y,t;Ri)\tilde{D}(x,y,t; R_i)D~(x,y,t;Ri)

denote the persistence-regulated drift field obtained after Physics-Anchored Drift Regulation (PADR) filtering.

PADR enforces multi-frame stability and suppresses transient fluctuation through deterministic conditioning mechanisms, including temporal persistence weighting and continuity constraints.

Only drift regions satisfying:

- Multi-frame persistence across defined temporal windows
- Spatial continuity consistent with physical scattering behavior
- Non-transient evolution under controlled illumination

are propagated forward into:

- Spatial partitioning (STRT),
- Directional coherence estimation (DIF), and
- Structured drift flux integration (SDF).

This conditioning ensures that subsequent components of the structured conformance vector v(t)\mathbf{v}(t)v(t) are derived from physically stable drift signatures rather than acquisition noise, illumination fluctuation, or single-frame perturbations.

It is important to distinguish this admissibility conditioning from the convergence evaluation performed by the State Convergence Engine (SCE). PADR governs physical stability of drift measurements within the SCF layer, whereas SCE evaluates trajectory and proximity of v(t)\mathbf{v}(t)v(t) relative to validated reference states.

By enforcing persistence before spatial and directional analysis, the architecture maintains deterministic robustness and measurement traceability across temporal acquisition sequences.

3.1.6 Summary

The structured drift field is defined as a deterministic transformation of the observed optical signal relative to a validated reference state:

D(x,y,t;Ri)=V(I(x,y,t),Ri)D(x,y,t; R_i) = \mathcal{V}\big(I(x,y,t), R_i\big)D(x,y,t;Ri)=V(I(x,y,t),Ri)

where V(·)\mathcal{V}(\cdot)V(·) denotes the reference-relative VAAD operator.

This transformation converts controlled optical measurement into a structured representation of measurable conformance displacement.

The drift field:

- Anchors deviation explicitly to validated reference geometry

- Preserves spatial topology across the measurement domain
- Enables directional coherence analysis via gradient structure
- Supports temporal modeling through accumulated drift and acceleration metrics
- Produces physically interpretable quantities grounded in measurable signal redistribution

Through persistence conditioning (PADR), the regulated drift field

$\tilde{D}(x,y,t; R_i)$

becomes the stable substrate from which all higher-order SCF components are derived.

It is important to distinguish architectural layers:

- The drift field and its derived metrics belong to the State Conformance Framework (SCF), which constructs the structured conformance vector $\mathbf{v}(t)$.
- The State Convergence Engine (SCE) operates on $\mathbf{v}(t)$, not directly on raw drift measurements.

Thus, the drift field constitutes the mathematical and physical foundation of the State Conformance Framework. All subsequent spatial, directional, temporal, and spectral modules derive their authority from its structured representation of measurable state displacement.

3.2 STRT — Spatial Topology Response Tracking

Spatial Topology Response Tracking (STRT) converts the persistence-conditioned drift field

$\tilde{D}(x,y,t; R_i)$

into a structured spatial activation representation suitable for deterministic topological analysis.

While the drift field quantifies measurable displacement relative to a validated reference state, STRT determines how that displacement is spatially organized across the domain.

Specifically, STRT:

- Partitions the surface into structured spatial tiles,
- Identifies regions exhibiting admissible drift activation,
- Constructs connected-component topology from activated regions, and
- Quantifies spatial spread, clustering, and boundary structure.

In this way, STRT transforms continuous drift magnitude into geographically accountable structure.

The drift field answers:
How much displacement exists relative to reference geometry?

STRT answers:
Where is that displacement spatially organized, and what is its topological structure?

This transition from continuous magnitude to structured spatial activation establishes the first geometric layer of the structured conformance vector $\mathbf{v}(t)$. It enables subsequent directional (DIF), flux (SDF), and temporal (DAI) analysis to operate on spatially coherent regions rather than isolated magnitude fluctuations.

Thus, STRT serves as the topological gateway between reference-relative drift measurement and higher-order conformance interpretation within the State Conformance Framework.

3.2.1 Mathematical Formulation of STRT (Tiling, Activation, Topology)

Let the persistence-conditioned drift field relative to a validated reference state R_i be:

$$\tilde{D}(x,y,t;R_i)$$

defined over an image domain $\Omega \subset \mathbb{R}^2$.

(a) Tile Partition Operator

Define a deterministic tile partition operator $\mathcal{T}$ that decomposes Ω into a grid of N non-overlapping tiles:

$$\mathcal{T}(\Omega) = \{\Omega_k\}_{k=1}^{N}, \quad \Omega = \bigcup_{k=1}^{N}\Omega_k,\quad \Omega_j \cap \Omega_k = \emptyset\ \text{for}\ j\neq k$$

Each tile Ω_k is typically a rectangular region of fixed dimensions $(s_x \times s_y)$, though other deterministic tessellations are admissible.

Define a tile-level drift statistic (one example is mean drift):

$$\mu_k(t) = \frac{1}{|\Omega_k|}\int_{\Omega_k}\tilde{D}(x,y,t;R_i)\,dA$$

Alternative deterministic tile statistics may be used (median, trimmed mean, percentile energy), provided they are explicitly defined.

(b) Activation Thresholding

Let $\theta(t)$ denote a deterministic activation threshold. In the simplest case, θ is constant; in calibrated deployments it may be derived from reference-state dispersion (e.g., a fixed multiple of reference variability).

Define a tile activation indicator:

$$a_k(t)= \begin{cases} 1, & \mu_k(t) \ge \theta(t) \\ 0, & \mu_k(t) < \theta(t) \end{cases}$$

The corresponding spatial activation map $M(x,y,t)$ is the piecewise-constant field:

$$M(x,y,t)=\sum_{k=1}^{N} a_k(t)\,\mathbf{1}_{\Omega_k}(x,y)$$

where $\mathbf{1}_{\Omega_k}(x,y)$ is the indicator function for tile Ω_k.

(c) Connected-Component Topology and Largest Component Ratio

Let the activated tile graph be defined by adjacency under 4-neighborhood or 8-neighborhood connectivity (chosen deterministically and held fixed). Let:

$$\mathcal{C}(t) = \{C_j(t)\}_{j=1}^{m(t)}$$

denote the set of connected components induced by the activated tiles $a_k(t)=1$, where each component $C_j(t)$ is a set of tile indices.

Define the size of a component as the number of tiles it contains:

$$|C_j(t)| = \text{cardinality of } C_j(t)$$

Let the total number of activated tiles be:

$$A(t)=\sum_{k=1}^{N} a_k(t)$$

Define the Largest Connected Component Ratio (LCC ratio):

$$L_{cc}(t)= \begin{cases} \frac{\max_j |C_j(t)|}{A(t)}, & A(t)>0 \\ 0, & A(t)=0 \end{cases}$$

This ratio quantifies whether activation is spatially concentrated into a coherent manifold (high L_{cc}) or dispersed into fragmented, isolated tiles (low L_{cc}).

STRT Outputs (Minimal Set)

The STRT module therefore deterministically produces:

- Activation map: M(x,y,t)M(x,y,t)M(x,y,t)
- Activated tile count: A(t)A(t)A(t)
- Connected component set: C(t)\mathcal{C}(t)C(t)
- Largest component ratio: Lcc(t)L_{cc}(t)Lcc(t)

These quantities form the topological substrate used by downstream modules (DIF, SDF, DAI), ensuring that directional and temporal analyses operate on spatially coherent activation structure rather than unstructured drift magnitude.

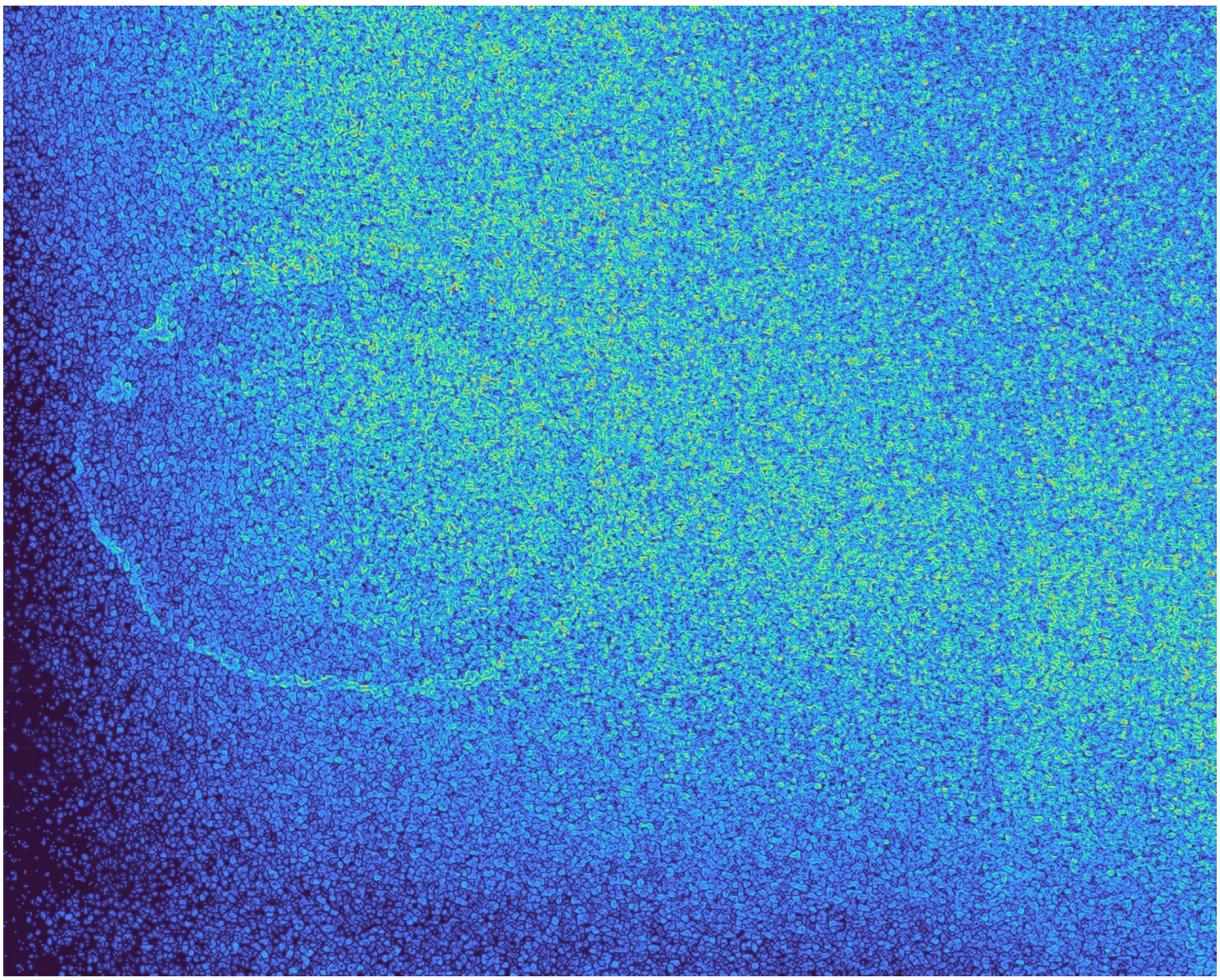

Figure 14. Drift Energy Heatmap with calibrated color scale. Structured circular boundary exhibits elevated drift energy relative to background field.

3.2.2 Connected Component Structure

Following binary mask formation

$M(x,y)$

STRT performs a connected-component decomposition over the activated region. Let

$\{CC_i\}$

denote the set of spatially contiguous activated regions identified within $M(x,y)$. Each connected component CC_i represents a geographically continuous deviation cluster relative to the reference state.

Define:

$\text{area}(CC_i)$

as the pixel area of the i^{th} component.

To quantify topological concentration, we define the **Largest Connected Component Ratio (** L_{cc} **)** as:

$$L_{cc} = \frac{\max_i \text{area}(CC_i)}{\sum_i \text{area}(CC_i)}$$

This metric expresses how strongly deviation energy concentrates into a dominant contiguous region relative to the total activated area.

Interpretation of L_{cc}

- **$L_{cc} \approx 1$**
  Deviation is spatially consolidated into a single dominant structure.
- **$L_{cc} \ll 1$**
  Deviation is fragmented across multiple small, disconnected regions.

Unlike simple activation counts, L_{cc} encodes the *organization* of deviation rather than its magnitude alone. Two surfaces may exhibit identical total activated area while possessing entirely different structural signatures depending on whether deviation is consolidated or dispersed.

Relevance in Thin-Film and Surface Contexts

In thin-film and scattering-field environments, topological organization provides critical diagnostic information:

Scenario	STRT Topological Signature
Coffee-ring boundary	High LccL_{cc}Lcc; continuous annular band
Distributed haze	Moderate LccL_{cc}Lcc; broad activation with partial connectivity
Sensor noise	Low LccL_{cc}Lcc; scattered micro-components
Localized crack or defect	High LccL_{cc}Lcc; small but dominant isolated cluster

A coffee-ring boundary, for example, typically manifests as a connected annular structure with high LccL_{cc}Lcc, even if the total activated area is moderate. In contrast, distributed haze may activate large portions of the field but produce lower structural consolidation.

Noise-induced activation tends to fragment into numerous micro-components, driving LccL_{cc}Lcc downward. Conversely, a localized crack yields a small overall activated area but a dominant connected cluster, resulting in elevated LccL_{cc}Lcc despite limited spatial extent.

Structural Implication

Connected component analysis transforms STRT from a binary deviation detector into a **topological classifier of deviation structure**. The system does not merely measure “how much” deviation exists; it measures how that deviation is spatially organized.

This distinction is essential for State Conformance evaluation. Conformance loss is not defined solely by magnitude but by structured divergence. A surface may exhibit measurable variation while retaining fragmented topology (suggestive of noise), whereas consolidated deviation with coherent structure more strongly indicates physical state transition.

Thus, LccL_{cc}Lcc provides a deterministic measure of deviation concentration, enabling STRT to encode spatial topology as part of the broader conformance architecture.

3.2.3 Additional Spatial Metrics

While binary activation and the Largest Connected Component Ratio LccL_{cc}Lcc capture primary topological structure, STRT may compute additional spatial descriptors to further characterize deviation geometry and distribution. These metrics provide complementary information regarding coverage, fragmentation, and morphological form.

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1. Activation Fraction

The **Activation Fraction** SSS is defined as:

S=∑x,yM(x,y)NS = \frac{\sum_{x,y} M(x,y)}{N}S=N∑x,yM(x,y)

where:

- $M(x,y)$ is the binary activation mask,
- N is the total pixel count in the observed region.

The metric S represents the proportion of the field that exceeds the deviation threshold relative to the defined reference state.

Interpretation:

- Low S → sparse or localized deviation.
- High S → widespread deviation across the surface.

Importantly, S measures *coverage*, not structure. Two surfaces may exhibit identical S values while differing substantially in topological organization. Therefore, S must be interpreted in conjunction with L_{cc} and connected-component metrics.

---

2. Connected Component Count

Let:

$$N_{cc} = \text{number of connected components in } M(x,y)$$

This metric quantifies fragmentation within the activated region.

Interpretation:

- Low N_{cc} with high L_{cc} → consolidated deviation.
- High N_{cc} with low L_{cc} → fragmented or stochastic activation.

Elevated N_{cc} values frequently indicate sensor noise, surface micro-texture, or threshold-induced speckling rather than structured physical state change. When used alongside persistence filters (PADR) and directional coherence metrics (DIF), N_{cc} assists in discriminating distributed noise from physically organized deviation.

---

3. Boundary Compactness

For each connected component CC_i, a **Boundary Compactness** metric may be computed:

$$C_i = \frac{P_i^2}{4\pi A_i}$$

where:

- P_i = perimeter of component CC_i,

- AiA_iAi = area of component CCiCC_iCCi.

This metric evaluates how closely a component approximates a compact geometric form.

Interpretation:

- Ci≈1C_i \approx 1Ci≈1 → approximately circular or compact structure.
- Large CiC_iCi → elongated, irregular, or ring-like geometry.

Boundary Compactness is particularly useful in thin-film and scattering contexts. For example:

- Coffee-ring boundaries often exhibit elevated CiC_iCi values due to annular geometry.
- Diffuse haze patches may produce moderate CiC_iCi values with lower perimeter-to-area ratios.
- Linear cracks or scratches generate high CiC_iCi due to elongated morphology.

Thus, compactness provides morphological discrimination independent of activation magnitude.

Structural Role Within State Conformance

Together, SSS, NccN_{cc}Ncc, LccL_{cc}Lcc, and CiC_iCi form a spatial descriptor set that characterizes deviation in terms of:

- Coverage (how much),
- Consolidation (how concentrated),
- Fragmentation (how dispersed),
- Morphology (what shape).

These metrics enable STRT to move beyond simple thresholding toward structured spatial interpretation. In the State Conformance framework, they support deterministic classification of deviation patterns while remaining anchored to measurable physical properties rather than probabilistic inference.

3.2.5 Deterministic Role Within SCF(t)\mathrm{SCF}(t)SCF(t)

Within the State Conformance Framework SCF(t)\mathrm{SCF}(t)SCF(t), STRT functions as the spatial foundation upon which higher-order structural and temporal analyses operate. Its role is not merely to detect threshold exceedance, but to impose geographic structure upon deviation.

STRT performs five essential deterministic transformations:

- **Magnitude → Geography**
  Scalar drift energy is mapped into explicit spatial coordinates.
- **Deviation → Topology**
  Binary activation and connected-component analysis convert variation into structured spatial forms.
- **Pixels → Regions**
  Deviation is elevated from individual pixel events to region-level entities capable of quantitative comparison.
- **Spatial Structure → Directional Input**
  Localized regions become inputs for Directional Instability Field (DIF) analysis, enabling coherent vector characterization.
- **Spatial Snapshots → Temporal Modeling**
  Region-level metrics provide stable primitives for temporal aggregation through Drift Acceleration Index (DAI) and related persistence models.

Without STRT, drift magnitude exists only as a scalar field—energetic but spatially unstructured. Such magnitude alone cannot distinguish distributed haze from localized fracture, nor coherent boundary formation from stochastic noise.

With STRT, deviation acquires structural identity. It becomes:

- **Localized —** tied to specific coordinates and bounded regions.
- **Quantified —** measurable in coverage, consolidation, and morphology.
- **Clustered —** organized into contiguous components rather than scattered pixels.
- **Geometrically characterized —** defined by area, perimeter, compactness, and connectivity.

This transformation is foundational. STRT converts raw drift magnitude into a structured spatial response, thereby enabling deterministic conformance evaluation within SCF(t)\mathrm{SCF}(t)SCF(t). It is the mechanism by which physical deviation is translated into interpretable spatial organization, allowing subsequent directional and temporal layers to operate on stable, region-based constructs rather than unstructured signal variation.

3.2.6 Validation Status

The current STRT implementation has been operationally validated with respect to its core spatial functions. The following components are fully implemented and active within the present framework:

- ✔ **Binary Pixel Activation**
  Threshold-based deviation masking relative to a defined reference state.
- ✔ **Connected Component Analysis**
  Extraction of contiguous deviation regions and computation of associated topological metrics (e.g., LccL_{cc}Lcc, cluster count).

These implemented elements provide sufficient spatial structure to support deterministic State Conformance evaluation, directional analysis (DIF), and temporal aggregation (DAI).

An optional architectural extension—referred to as **Tile-Only STRT Mode**—remains under consideration for future enhancement. In this configuration, activation would be evaluated at the structured tile level rather than at the pixel level. Each tile would function as a metrology-aligned unit of spatial aggregation.

Potential advantages of tile-level STRT include:

- **Metrology-Aligned Partitioning**
  Coarser spatial segmentation aligned with inspection grids, process zones, or manufacturing subregions.
- **Region-of-Interest (ROI) Refinement**
  Hierarchical subdivision of selected tiles for targeted analysis.
- **Computational Scaling**
  Reduced processing overhead for large-area surfaces through controlled spatial resolution.

Importantly, tile-only STRT is not required for the validity of the current State Conformance implementation. The existing pixel-based STRT provides deterministic spatial localization and topological characterization sufficient for present validation objectives. The tile-based extension is therefore architectural in nature—intended to enhance scalability and operational flexibility rather than to correct any structural limitation of the core method.

3.2.7 Summary

STRT formalizes spatial deviation as a measurable topological construct within the State Conformance Framework.

Binary activation is defined as:

M(x,y)=1(D(x,y)>τ)M(x,y) = \mathbb{1}\big(D(x,y) > \tau\big)M(x,y)=1(D(x,y)>τ)

where D(x,y)D(x,y)D(x,y) represents the drift field and τ\tauτ is the defined deviation threshold.

Topological concentration is quantified through the Largest Connected Component Ratio:

Lcc=maxiarea(CCi)∑iarea(CCi)L_{cc} = \frac{\max_i \text{area}(CC_i)}{\sum_i \text{area}(CC_i)}Lcc=∑iarea(CCi)maxiarea(CCi)

where CCiCC_iCCi denotes each spatially contiguous activated region.

Through thresholding and connected-component analysis, STRT converts the continuous drift field into a structured spatial response map. Deviation is no longer an unbounded scalar field but becomes:

- Explicitly localized,
- Partitioned into contiguous regions,
- Quantified by coverage and consolidation, and
- Geometrically characterized through measurable topology.

In doing so, STRT resolves the foundational State Conformance question:

Where is deviation occurring, and how is it spatially organized relative to the defined reference state?

This spatial grounding is indispensable. Directional analysis (DIF), spectral redistribution (SLE), and temporal aggregation (DAI) all depend upon stable regional primitives derived from STRT. Without spatial structuring, subsequent coherence and persistence modeling would operate on unstructured magnitude alone.

STRT therefore constitutes the spatial backbone of the SCF architecture, enabling deterministic, geography-aware conformance evaluation across time.

3.3 DIF (Directional Integrity Field)

Where STRT establishes *where* deviation occurs, DIF evaluates *how* that deviation is structurally organized.

Spatial magnitude alone does not establish material transition. Elevated drift energy may arise from transient lighting fluctuation, sensor noise, or stochastic surface texture. Such variation may be measurable, but it lacks directional coherence.

Physical processes, by contrast, tend to manifest as structured gradients. Evaporative transport produces outward flux. Stress propagation exhibits directional accumulation. Boundary formation generates coherent transition bands. Crack initiation follows aligned instability vectors. These phenomena do not merely increase magnitude—they impose directional organization upon the field.

The Directional Integrity Field (DIF) is designed to quantify this distinction.

DIF operates on localized regions identified by STRT and evaluates the coherence, orientation stability, and reinforcement behavior of drift vectors within those regions. It determines whether deviation forms:

- A coherent directional field consistent with physical transport or propagation, or
- A stochastic pattern lacking structural reinforcement.

In this sense, DIF acts as a structural discriminator. It distinguishes physically admissible instability from unstructured fluctuation.

Within the State Conformance Framework, DIF therefore answers the second foundational question:

Is the observed deviation directionally organized in a manner consistent with material state change?

By introducing directional coherence into the evaluation loop, DIF transforms deviation analysis from magnitude assessment into structural validation. It provides the necessary bridge between spatial localization (STRT) and temporal persistence modeling (DAI), ensuring that only directionally meaningful instability contributes to higher-order conformance metrics.

3.3.1 Gradient-Based Vector Field

Let the drift field be denoted by:

D(x,y)D(x,y)D(x,y)

To evaluate directional structure, the spatial gradient of the drift field is computed:

∇D(x,y)=[∂D∂x,∂D∂y]\nabla D(x,y) = \left[\frac{\partial D}{\partial x}, \frac{\partial D}{\partial y} \right]∇D(x,y)=[∂x∂D,∂y∂D]

This operation produces a local vector field:

G⃗(x,y)=∇D(x,y)\vec{G}(x,y) = \nabla D(x,y)G(x,y)=∇D(x,y)

where each vector encodes the direction and rate of maximum spatial change in drift magnitude.

Two quantities are derived from this field:

- **Magnitude**

  ∣G⃗(x,y)∣=(∂D∂x)2+(∂D∂y)2|\vec{G}(x,y)| = \sqrt{\left(\frac{\partial D}{\partial x}\right)^2 + \left(\frac{\partial D}{\partial y}\right)^2}∣G(x,y)∣=(∂x∂D)2+(∂y∂D)2

  representing the local rate of spatial drift variation.

- **Orientation**

$$\theta(x,y) = \tan^{-1} \left(\frac{\partial D / \partial y} {\partial D / \partial x} \right)$$

representing the directional angle of the local gradient vector.

The resulting gradient field characterizes the **local directional flow of drift energy** across the surface. Whereas STRT determines *where* deviation occurs, the gradient field determines *how that deviation is directionally structured*.

Physical Interpretation

Distinct physical phenomena generate characteristic directional signatures:

- **Ring boundaries**
  Exhibit coherent tangential alignment along the boundary band.
- **Cracks or fractures**
  Produce longitudinal alignment along the instability axis.
- **Diffuse haze or thin-film redistribution**
  Characterized by low-magnitude gradients with weak directional coherence.
- **Sensor noise or stochastic fluctuation**
  Produces random orientation distributions with no dominant angular structure.

The gradient-based vector field therefore serves as the foundational input to DIF coherence metrics. It transforms scalar drift into a directional representation, enabling quantitative discrimination between organized physical processes and unstructured variation.

3.3.2 Directional Coherence Metric

To quantify directional organization within the gradient field, DIF evaluates the angular coherence of local drift vectors.

Let:

- θ_i denote the orientation of the gradient vector at pixel i,
- w_i denote the associated weight at pixel i, typically defined as:

$$w_i = |\vec{G}_i|$$

where $|\vec{G}_i|$ is the magnitude of the gradient at that location.

Directional coherence K is defined as:

$$K = \frac{\left| \sum_i w_i e^{j\theta_i} \right|}{\sum_i w_i}$$

where:

- $e^{j\theta_i}$ maps each orientation onto the unit circle in the complex plane,
- j is the imaginary unit,
- $0 \le K \le 1$.

This formulation computes the magnitude of the weighted mean resultant vector of all local orientations, normalized by total weight.

Interpretation of K

K Value	Interpretation
$K \approx 1$	Strong directional alignment across the region
$K \approx 0$	Random or isotropic orientation distribution
Intermediate K	Partial coherence or mixed directional structure

A high K value indicates that gradient vectors reinforce a common directional trend, consistent with organized physical processes such as crack propagation, boundary formation, or stress accumulation. A low K value indicates angular dispersion typical of noise or diffuse, unstructured variation.

Deterministic Role

Although mathematically related to circular statistics, this formulation is applied deterministically to physically derived gradient fields. It does not infer probabilistic alignment; rather, it measures the structural coherence of drift gradients relative to the observed state.

Directional coherence therefore provides a quantitative discriminator between organized instability and stochastic fluctuation, serving as the principal structural metric within the DIF layer of the State Conformance Framework.

3.3.3 Physical Interpretation

The Directional Integrity Field (DIF) evaluates whether local drift gradients reinforce a common directional structure. It measures the degree to which drift vectors align and collectively express organized behavior rather than independent fluctuation.

A high coherence value KKK indicates that directional vectors exhibit constructive reinforcement across the evaluated region. Such reinforcement is characteristic of physically meaningful processes, including:

- Organized material transport,
- Progressive structural propagation,
- Boundary consolidation,
- Stress-aligned accumulation or fracture precursors.

In these cases, deviation is not merely present—it is directionally structured and spatially coherent.

Conversely, a low coherence value KKK indicates angular dispersion among gradient vectors. This pattern is consistent with:

- Stochastic surface texture,
- Sensor-induced noise,
- Illumination fluctuation,
- Non-structural or transient variation.

Low coherence therefore signals the absence of organized physical behavior, even if drift magnitude is measurable.

Example: IPA Ring Experiment

The IPA deposition experiment provides a clear illustration of DIF behavior across distinct spatial zones:

- **Boundary Band**
  Exhibits elevated KKK values due to strong tangential alignment of gradient vectors along the ring perimeter. The directional field reinforces the annular structure.
- **Interior Haze Region**
  Typically produces moderate-to-low KKK values. Drift magnitude may be present, but directional reinforcement is weaker and less organized.
- **Exterior Reference Region**
  Yields near-zero KKK, reflecting the absence of structured deviation and confirming baseline conformance.

This layered differentiation demonstrates the functional role of DIF: it distinguishes physically organized deviation from magnitude-only activation. Two regions may exhibit comparable activation levels, yet DIF reveals whether that activation reflects structured instability or uncorrelated variation.

Within the State Conformance Framework, DIF therefore serves as the structural validator of spatial deviation, ensuring that only directionally coherent phenomena contribute to higher-order conformance and temporal persistence metrics.

3.3.4 PQRC Overlay Interpretation

The PQRC overlay provides a visual encoding of the Directional Integrity Field by rendering local gradient vectors directly onto the spatial response map.

Within this visualization:

- **Arrow Direction**
  Each arrow represents the local gradient vector $\vec{G}(x,y)$, indicating the direction of maximum spatial change in drift magnitude.
- **Arrow Length (or Intensity)**
  Encodes gradient magnitude $|\vec{G}(x,y)|$, reflecting the rate of spatial variation in drift energy.
- **Arrow Density**
  Corresponds to STRT activation regions. Arrows are rendered primarily within spatial zones identified as exceeding the deviation threshold, ensuring that directional analysis is geographically grounded.
- **Arrow Alignment**
  Provides an intuitive visual correlate of the directional coherence metric K.
  Highly aligned arrows indicate strong coherence (high K), whereas dispersed or randomly oriented arrows indicate low coherence (low K).

The PQRC overlay therefore serves as a structured interpretive bridge between quantitative metrics and human inspection. It translates mathematical gradient and coherence calculations into a spatially intuitive representation while preserving deterministic alignment with underlying drift measurements.

Within the State Conformance Framework, the overlay is not merely illustrative; it is a visual confirmation of directional structure, reinforcing the distinction between organized physical instability and unstructured variation.

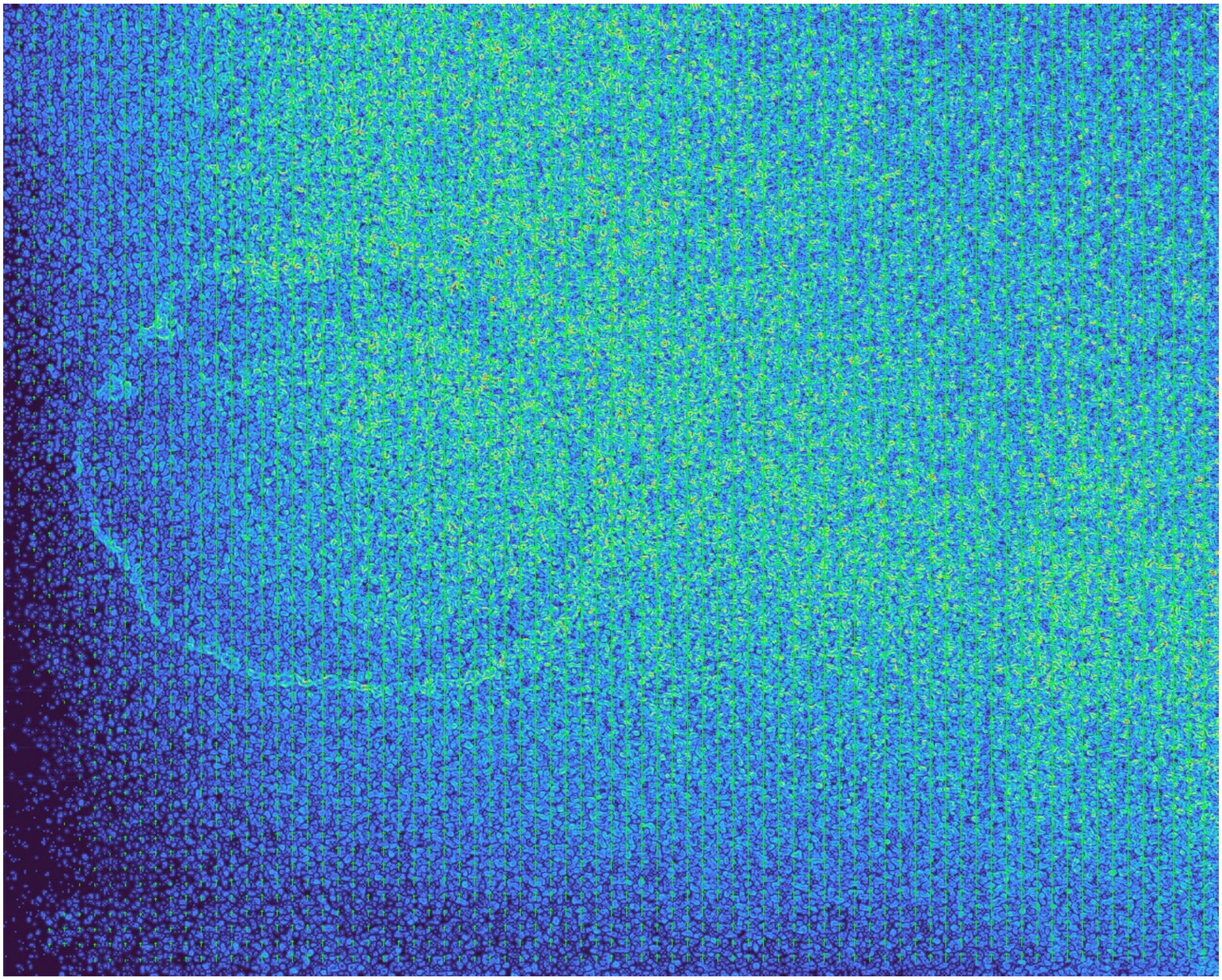

Figure 15. PQRC Overlay and Directional Coherence Map

Left: Gradient vector overlay derived from ∇D(x,y)\nabla D(x,y)∇D(x,y).
Right: Directional coherence heatmap indicating regions of high structural alignment.

3.3.5 Deterministic Role Within SCF(t)\mathrm{SCF}(t)SCF(t)

Within the State Conformance Framework SCF(t)\mathrm{SCF}(t)SCF(t), DIF functions as the structural validation layer. Whereas STRT establishes the spatial presence of deviation, DIF evaluates whether that deviation exhibits directional organization consistent with physical causality.

DIF addresses the critical question:

Is the observed deviation directionally structured in a manner consistent with material process behavior?

In the absence of DIF, all threshold exceedances would be treated equivalently. Spatial magnitude alone would lack structural discrimination, and transient fluctuations could be misinterpreted as meaningful state change.

With DIF integrated:

- **Stochastic noise is suppressed** through low coherence evaluation.
- **Organized physical processes are elevated** when directional reinforcement is present.
- **Boundary-driven phenomena are distinguished from diffuse haze**, even when activation magnitude is similar.

By introducing directional coherence analysis, DIF converts spatial deviation into structural evidence. It ensures that only directionally admissible instability contributes to higher-order conformance metrics, including persistence modeling and acceleration analysis.

In this way, DIF provides the structural legitimacy required for deterministic State Conformance evaluation. It transforms drift magnitude from a spatial signal into a physically interpretable instability field, enabling rigorous separation between noise, distributed fluctuation, and coherent material transition.

3.3.6 Validation Status

The current DIF implementation has been validated at the gradient-coherence level within controlled experimental conditions. Implementation status is as follows:

- **✔ Gradient-Based Coherence Metric Implemented**
  Spatial gradients are computed from the drift field and evaluated using the weighted directional coherence metric KKK. This functionality is active and integrated within the SCF pipeline.
- **☐ Lighting-Neutral Vector Validation Pending**
  Final vector-field neutrality validation is scheduled under a symmetric four-strip darkfield configuration. This configuration is intended to reduce illumination bias and confirm directional stability under controlled lighting geometry.
- **☐ Divergence and Curl Metrics (Roadmap Extension)**
  Higher-order vector-field diagnostics are planned as architectural extensions.

Future extensions may compute:

$\nabla\cdot\vec{G}$ (divergence)\nabla \cdot \vec{G} \quad \text{(divergence)}∇⋅G(divergence) $\nabla\times\vec{G}$(curl)\nabla \times \vec{G} \quad \text{(curl)}∇×G(curl)

These operators would enable additional structural discrimination within the gradient field:

- **Divergence** may identify radial accumulation or deposition patterns, such as evaporative transport toward or away from a boundary.
- **Curl** may detect rotational or shear-like flow structures within the drift field.

Such extensions would enhance the physical interpretability of directional structure, allowing differentiation between radial deposition dynamics and rotational or swirling flow behavior.

Importantly, these higher-order metrics are roadmap enhancements rather than prerequisites for current validation. The implemented gradient-based coherence metric KKK is sufficient to establish directional organization within the present State Conformance architecture.

3.4 DAI (Drift Acceleration Index)

If STRT determines **where** deviation occurs and DIF determines **whether that deviation is directionally structured**, the Drift Acceleration Index (DAI) determines **how that deviation evolves over time**.

Spatial localization and directional coherence establish structural admissibility at a given moment. However, physical state transition is inherently temporal. Material processes such as transport, stress accumulation, film redistribution, and fracture initiation do not occur instantaneously; they manifest as progressive change across successive observations.

DAI introduces this temporal dimension into the State Conformance Framework.

By evaluating the rate of change—and the acceleration—of structured drift metrics over time, DAI transforms SCF from a static measurement architecture into a dynamic monitoring system. It distinguishes:

- Stable deviation from growing instability,
- Transient fluctuation from persistent accumulation,
- Linear progression from accelerating structural transition.

In this way, DAI enables predictive interpretation rather than post-event detection. It quantifies whether instability is merely present, or whether it is intensifying in a manner consistent with imminent state transition.

Within the SCF architecture, DAI therefore completes the triad:

- **STRT —** spatial localization,
- **DIF —** structural organization,
- **DAI —** temporal evolution.

Together, these layers enable deterministic, physics-anchored monitoring of material conformance across space, structure, and time.

3.4.1 Temporal Derivatives

Let P(t)P(t)P(t) denote a structured drift metric evaluated over time.
The function P(t)P(t)P(t) may represent any spatially and directionally validated quantity derived from STRT and DIF, such as activation fraction, coherence-weighted drift flux, or region-constrained instability magnitude.

The **first temporal derivative** is defined as:

DAI1(t)=dP(t)dtDAI_1(t) = \frac{dP(t)}{dt}DAI1(t)=dtdP(t)

The **second temporal derivative** is defined as:

DAI2(t)=d2P(t)dt2DAI_2(t) = \frac{d^2P(t)}{dt^2}DAI2(t)=dt2d2P(t)

where:

- DAI1(t)DAI_1(t)DAI1(t) represents the **instability growth rate**, and
- DAI2(t)DAI_2(t)DAI2(t) represents the **instability acceleration**.

Interpretation

- DAI1(t)>0DAI_1(t) > 0DAI1(t)>0 indicates increasing structured deviation.
- DAI1(t)≈0DAI_1(t) \approx 0DAI1(t)≈0 indicates stability or steady-state behavior.
- DAI1(t)<0DAI_1(t) < 0DAI1(t)<0 indicates relaxation or recovery.

The second derivative provides additional predictive power:

- DAI2(t)>0DAI_2(t) > 0DAI2(t)>0 indicates accelerating instability accumulation.
- DAI2(t)<0DAI_2(t) < 0DAI2(t)<0 indicates decelerating growth or stabilization.

By incorporating first- and second-order temporal behavior, DAI enables discrimination between transient fluctuation, linear progression, and accelerating state transition.

Within the State Conformance Framework, these derivatives elevate structured drift metrics from static descriptors to dynamic indicators of material evolution.

3.4.2 Candidate Drift Metrics

The temporal function P(t)P(t)P(t) used in DAI analysis may represent any structured drift quantity derived from the spatial and directional layers of the State Conformance Framework.

Representative candidates include:

- **Mean Drift Magnitude**
  driftmean(t)\text{drift}_{\text{mean}}(t)driftmean(t), representing average deviation energy across the observed region.
- **Upper Quantile Drift (e.g., p95)**
  driftp95(t)\text{drift}_{p95}(t)driftp95(t), capturing high-percentile deviation behavior and emphasizing emergent extremes.
- **STRT Activation Fraction**
  S(t)S(t)S(t), reflecting temporal evolution of spatial coverage above threshold.
- **DIF Directional Coherence**
  K(t)K(t)K(t), representing the evolution of directional organization within activated regions.

These examples illustrate that DAI is not restricted to scalar magnitude tracking. It may operate on spatial topology metrics (e.g., activation coverage), structural coherence metrics (e.g., directional alignment), or composite structured quantities derived from the SCF pipeline.

Accordingly, DAI provides a generalized temporal operator applicable to magnitude, topology, and coherence alike. Its role is to quantify how structured deviation evolves—not merely how large it becomes.

3.4.3 Physical Interpretation

The Drift Acceleration Index (DAI) enables structured interpretation of temporal evolution by distinguishing growth, stabilization, and recovery regimes.

Case 1: Emerging Instability

- DAI1(t)>0DAI_1(t) > 0DAI1(t)>0
- DAI2(t)>0DAI_2(t) > 0DAI2(t)>0

This condition indicates that structured deviation is increasing and doing so at an accelerating rate. Such behavior is characteristic of early-stage instability accumulation, where physical processes reinforce themselves over successive observations. Examples include progressive stress alignment, material transport concentration, or boundary consolidation.

Case 2: Stabilization

- DAI2(t)>0DAI_1(t) > 0DAI1(t)>0
- DAI2(t)<0DAI_2(t) < 0DAI2(t)<0

Here, deviation continues to increase, but the rate of increase is declining. This pattern is consistent with systems approaching equilibrium or saturation. Growth remains present, yet reinforcement weakens over time, suggesting transition toward a steady-state configuration.

Case 3: Conformance Recovery

- DAI1(t)<0DAI_1(t) < 0DAI1(t)<0

A negative first derivative indicates decay of structured deviation. This behavior may occur following removal of a disturbance, post-cleaning surface normalization, or relaxation of accumulated stress. In this regime, the system trends back toward baseline conformance.

Example: IPA Evaporation Experiment

The IPA deposition experiment illustrates these temporal phases clearly:

- **Initial Deposition**
  Positive DAI1DAI_1DAI1, indicating growth of structured deviation.
- **Ring Formation Phase**
  Drift metrics approach a peak as boundary structure consolidates.
- **Evaporation Stabilization**
  DAI1→0DAI_1 \rightarrow 0DAI1→0 and DAI2<0DAI_2 < 0DAI2<0, reflecting decelerating change as the system stabilizes.

This temporal signature confirms a genuine state transition rather than a transient fluctuation. The presence of structured acceleration followed by deceleration is indicative of physically governed process dynamics, not stochastic noise.

3.4.4 Discrete Implementation

In practical operation, drift metrics are evaluated over discrete frame intervals rather than continuous time. Let tkt_ktk denote the timestamp of the kthk^{\text{th}}kth frame and Δt=tk−tk−1\Delta t = t_k - t_{k-1}Δt=tk−tk−1 represent the frame interval.

The first temporal derivative may be approximated using a finite-difference formulation:

DAI1(tk)≈P(tk)−P(tk−1)ΔtDAI_1(t_k) \approx \frac{P(t_k) - P(t_{k-1})}{\Delta t}DAI1(tk)≈ΔtP(tk)−P(tk−1)

The second temporal derivative may be approximated as:

DAI2(tk)≈P(tk)−2P(tk−1)+P(tk−2)(Δt)2DAI_2(t_k) \approx \frac{P(t_k) - 2P(t_{k-1}) + P(t_{k-2})}{(\Delta t)^2}DAI2(tk)≈(Δt)2P(tk)−2P(tk−1)+P(tk−2)

These discrete formulations provide stable numerical estimates of growth rate and acceleration using sequential observations.

Importantly, this implementation preserves deterministic behavior. The system does not rely on probabilistic forecasting or learned predictive models. Instead, it evaluates measurable changes between successive structured drift states.

As a result, DAI remains fully grounded in observed data. Temporal interpretation emerges directly from finite differences of physically derived metrics, ensuring compatibility with the deterministic principles of the State Conformance Framework.

3.4.5 Deterministic Role Within SCF(t)\mathrm{SCF}(t)SCF(t)

Within the State Conformance Framework SCF(t)\mathrm{SCF}(t)SCF(t), DAI provides the temporal validation layer. Whereas STRT establishes spatial localization and DIF confirms structural admissibility, DAI determines how structured deviation evolves across successive observations.

Specifically, DAI enables:

- **Early Instability Detection**
  Identification of accelerating deviation before visible defect manifestation.
- **Transition Identification**
  Recognition of regime changes, including onset, peak formation, and stabilization phases.
- **Process Stabilization Confirmation**
  Verification that growth rates are decelerating and approaching equilibrium.
- **Recovery Validation**
  Quantification of deviation decay following disturbance removal or corrective intervention.

By evaluating temporal derivatives of structured drift metrics, DAI ensures that SCF(t)\mathrm{SCF}(t)SCF(t) reflects dynamic process behavior rather than isolated threshold exceedance.

In the absence of DAI, conformance assessment would be limited to static snapshots. With DAI integrated, the framework captures directional change over time—distinguishing transient fluctuation from progressive instability and equilibrium from recovery.

DAI therefore completes the spatial–structural–temporal triad of the State Conformance Framework, enabling deterministic monitoring of evolving material states.

3.4.6 Validation Status

The Drift Acceleration Index has been formally defined within the State Conformance Framework and integrated at the metric level. Current implementation status is as follows:

- ✔ **Temporal Derivative Metric Defined**
  First- and second-order finite-difference formulations for DAI1(t)DAI_1(t)DAI1(t) and DAI2(t)DAI_2(t)DAI2(t) have been specified and incorporated into the SCF architecture.
- ☐ **Multi-Frame Temporal Validation Pending**
  Controlled experimental validation across extended capture sequences remains in progress.

Planned validation activities include:

- **Controlled Deposition Sequences**
  Time-resolved acquisition during material deposition or redistribution to observe accelerating and decelerating regimes.
- **Cleaning and Recovery Cycles**
  Structured removal of induced deviation to validate negative derivative behavior and recovery signatures.
- **Time-Resolved Conformance Tracking**
  Continuous monitoring across multiple frames to confirm stable detection of growth, peak formation, stabilization, and decay phases.

These validation steps are intended to confirm that DAI reliably distinguishes transient fluctuation from sustained and accelerating structural change under controlled experimental conditions.

The underlying mathematical formulation is complete; ongoing validation focuses on empirical confirmation across reproducible temporal sequences.

Integrated View

Together:

Module	Domain	Question
STRT	Space	Where is deviation?
DIF	Structure	Is it physically coherent?
DAI	Time	Is it growing or stabilizing?

This tri-layer integration transforms drift magnitude into:

- Spatially accountable
- Structurally validated
- Temporally tracked

state conformance evidence.

It is this integration—not magnitude alone—that differentiates the State Conformance Engine from anomaly detection systems.

4. Spectral Loss Extension (SLE)

The drift field D(x,y)D(x,y)D(x,y) captures spatial deviation magnitude, and DIF evaluates directional organization within that deviation. However, not all physically meaningful surface changes manifest primarily as directional gradients.

Certain classes of material transformation present instead as attenuation or redistribution of high-frequency spatial content. In such cases, directional coherence may be weak or absent, yet measurable spectral degradation occurs relative to a defined reference state.

Representative examples include:

- Thin-film haze formation,
- Micro-layer deposition,
- Surface wetting or fluid redistribution,
- Texture softening due to coating or contamination,
- Blur induced by refractive or scattering-layer modification.

These phenomena reduce fine-scale spatial contrast rather than generate strong directional gradients. As a result, gradient-based coherence metrics alone may underestimate their structural impact.

The Spectral Loss Extension (SLE) addresses this domain by quantifying high-frequency spectral attenuation relative to the reference condition. Rather than focusing on vector-field structure, SLE evaluates changes in spatial frequency energy distribution, enabling detection of subtle but physically significant texture degradation.

Within the State Conformance Framework, SLE complements STRT, DIF, and DAI by introducing an energetic-frequency dimension. Where STRT localizes deviation, DIF validates directional structure, and DAI tracks temporal evolution, SLE captures spectral redistribution effects that manifest as texture loss or blur.

SLE therefore expands SCF beyond gradient-dominated phenomena, ensuring that conformance assessment includes both structural and spectral domains of surface change.

4.1 High-Frequency Energy Model

Let:

- $HF_{\text{golden}}(x,y)$ denote the high-frequency energy distribution of the validated reference state, and
- $HF_{\text{current}}(x,y)$ denote the corresponding high-frequency energy distribution of the observed frame.

High-frequency energy may be estimated using one or more physically grounded operators, including:

- Laplacian magnitude response,
- High-pass filtered spatial response,
- Localized Fourier band energy (FFT-based),
- Wavelet high-band coefficient energy.

Each method extracts fine-scale spatial variation associated with texture sharpness and edge content.

The Spectral Loss Extension (SLE) is defined pointwise as:

$$SLE(x,y) = \max\left(0,\, HF_{\text{golden}}(x,y) - HF_{\text{current}}(x,y) \right)$$

This formulation quantifies attenuation of high-frequency content relative to the baseline state. Positive values indicate spectral loss—i.e., reduction of fine spatial detail—while zero indicates preservation or amplification of high-frequency energy.

The use of the $\max(0, \cdot)$ operator ensures that only spectral degradation is recorded. Amplification of high-frequency components, which may arise from noise or sharpening artifacts, does not contribute positively to SLE.

In this manner, SLE provides a deterministic measure of texture degradation or blur, complementing gradient-based structural analysis within the broader State Conformance Framework.

4.2 Physical Interpretation

High-frequency energy encodes fine-scale spatial structure within a surface. It is directly associated with:

- Micro-texture features,
- Edge sharpness and contrast transitions,
- Fine structural detail,
- Micro-roughness-induced scattering behavior.

On matte or textured substrates, high-frequency content arises from small-scale surface irregularities that scatter light and produce measurable spatial contrast.

When a thin film redistributes across such a surface, several physical changes may occur:

- Micro-contrast is reduced,
- High-frequency scattering diminishes,
- Fine texture detail becomes attenuated,
- The surface visually appears hazed or softened.

Crucially, this transformation may not generate strong directional gradients. The redistribution can be diffuse and isotropic, lacking coherent vector alignment.

Under these conditions:

- The drift field D(x,y)D(x,y)D(x,y) may exhibit only moderate magnitude change,
- DIF coherence KKK may remain low due to absence of directional reinforcement,
- Yet SLE will produce a strong positive response reflecting measurable loss of high-frequency energy.

SLE therefore captures texture degradation independent of directional coherence. It detects spectral attenuation even when gradient-based structure is weak or absent.

Within the State Conformance Framework, SLE serves as the spectral complement to STRT and DIF—ensuring that isotropic texture collapse and haze formation are identified even in the absence of organized directional flow.

4.3 Distinguishing Edge Shift vs. Texture Collapse

A primary motivation for the Spectral Loss Extension (SLE) is to differentiate between two fundamentally distinct surface phenomena: structural relocation and spectral attenuation.

These processes may produce superficially similar drift magnitudes yet arise from entirely different physical mechanisms.

Case A — Edge Shift (Structural Relocation)

Edge shift occurs when a boundary or structural feature moves or deforms without significant degradation of fine-scale texture. This may result from boundary displacement, crack propagation, or structural realignment.

Characteristic features include:

- Boundary displacement or geometric relocation,
- Strong gradient magnitude,
- High directional coherence,
- Minimal loss of high-frequency texture content.

Signature Profile:

- High D(x,y)D(x,y)D(x,y) magnitude,
- High directional coherence KKK,
- Low SLE response.

In this case, deviation is structurally organized and directionally reinforced, yet fine-scale spectral energy remains largely preserved.

Case B — Texture Collapse (Thin Film / Blur)

Texture collapse arises when a thin film, wetting layer, or scattering medium redistributes across the surface, attenuating micro-contrast without inducing strong directional gradients.

Characteristic features include:

- Distributed smoothing or haze,
- Reduced micro-texture contrast,
- Weak or diffuse gradient structure,
- Significant high-frequency attenuation.

Signature Profile:

- Moderate D(x,y)D(x,y)D(x,y) magnitude,
- Low-to-moderate directional coherence KKK,
- High SLE response.

Here, the dominant change is spectral redistribution rather than geometric relocation.

Structural Importance

This distinction is critical in haze detection, thin-film validation, and micro-texture monitoring. Without SLE, distributed blur may appear as a weak or ambiguous anomaly when evaluated solely through magnitude and coherence metrics. With SLE integrated, spectral attenuation becomes directly measurable and structurally attributable.

SLE therefore prevents isotropic texture collapse from being misclassified as low-importance variation. It elevates spectral redistribution to a first-class diagnostic signal within the State Conformance Framework.

4.4 Spatial Aggregation Metrics

As with STRT and DIF, the Spectral Loss Extension (SLE) supports aggregation from pixel-level measurements to region-level descriptors. These aggregated metrics enable integration of spectral behavior into the broader State Conformance architecture.

A fundamental aggregate measure is the **mean spectral loss**:

SLEmean=1N∑x,ySLE(x,y)SLE_{\text{mean}} = \frac{1}{N} \sum_{x,y} SLE(x,y)SLEmean=N1
x,y∑SLE(x,y)

where NNN denotes the total number of evaluated pixels. This metric captures the average degree of high-frequency attenuation across the observed region.

To emphasize localized or emergent degradation, percentile-based measures may also be employed, such as:

SLEp95SLE_{p95}SLEp95

which represents the 95th percentile of spectral loss values. This formulation highlights extreme attenuation zones without being overly influenced by isolated outliers.

In addition, spatial connectivity analysis may be applied to the SLE field to derive a **connected spectral-loss area metric**:

SLEareaSLE_{\text{area}}SLEarea

representing the total area of contiguous regions exceeding a defined spectral-loss threshold. This enables discrimination between diffuse low-level attenuation and consolidated spectral collapse.

Together, these aggregated measures provide spectral descriptors analogous to STRT's spatial topology metrics and DIF's coherence metrics. They allow SLE outputs to be incorporated directly into SCF(t)\mathrm{SCF}(t)SCF(t) as the spectral component of structured deviation analysis.

By elevating spectral loss from a pointwise measure to a region-level construct, SLE maintains architectural consistency with the spatial and directional layers of the State Conformance Framework.

4.5 Relationship to the Drift Field

Although SLE is derived from spatial image structure, it is not redundant with the drift field D(x,y)D(x,y)D(x,y). Each component of the State Conformance Framework measures a distinct physical aspect of deviation.

Component	Primary Measurement Domain
Drift Field D(x,y)D(x,y)D(x,y)	Deviation magnitude
DIF	Directional organization
SLE	High-frequency spectral attenuation

The drift field quantifies overall spatial deviation relative to a reference state. DIF evaluates whether that deviation exhibits coherent directional structure. SLE, by contrast, measures loss of fine-scale texture energy—an energetic redistribution effect rather than a gradient-driven one.

In practical scenarios:

- Drift magnitude may increase due to edge formation, crack propagation, or boundary displacement without significant spectral attenuation.
- SLE may increase due to surface softening, wetting, or thin-film haze even when directional coherence remains weak.
- In severe film redistribution or advanced surface degradation, both drift magnitude and spectral loss may increase simultaneously.

The independence of SLE from gradient-based metrics enhances diagnostic resolution. By separating magnitude, structure, and spectral attenuation into distinct analytical channels, the framework avoids conflating edge relocation with texture collapse.

SLE therefore improves interpretive clarity within SCF(t), ensuring that isotropic micro-texture degradation is recognized as a measurable and physically meaningful form of state deviation.

4.6 Deterministic Role Within SCF(t)\mathrm{SCF}(t)SCF(t)

The Spectral Loss Extension (SLE) expands the State Conformance Framework into the spectral domain. While STRT localizes deviation and DIF validates directional structure, SLE evaluates degradation of fine-scale spatial energy relative to a validated reference state.

SLE addresses the question:

Has fine-scale surface structure attenuated relative to baseline?

This capability is particularly important in applications where deviation manifests as texture softening rather than geometric displacement, including:

- Haze validation on optical or matte surfaces,
- Cleaning verification and residue detection,
- Thin wet-film or micro-layer identification,
- Coating uniformity assessment,
- Subtle material absorption or scattering changes.

In such cases, directional coherence may remain weak and gradient magnitude moderate, yet spectral redistribution is measurable and physically meaningful.

Because SLE is defined relative to a calibration-validated reference frame, its operation remains fully deterministic. It does not rely on statistical learning, adaptive inference, or trained classification models. Spectral loss is computed directly from measurable high-frequency energy differences under controlled acquisition conditions.

By preserving reference-defined computation, SLE maintains alignment with the deterministic principles of the State Conformance Framework while extending its analytical reach into micro-texture and spectral integrity evaluation.

4.7 Integration into SCF(t)\mathrm{SCF}(t)SCF(t)

Recall the generalized State Conformance formulation:

SCF(t)=f(STRT,DIF,DAI,PADR,SLE)\mathrm{SCF}(t) = f\big(\text{STRT}, \text{DIF}, \text{DAI}, \text{PADR}, \text{SLE} \big)SCF(t)=f(STRT,DIF,DAI,PADR,SLE)

Within this architecture, SLE introduces the **spectral redistribution axis** of conformance evaluation.

Each component contributes a distinct analytical dimension:

- **Space —** STRT localizes deviation geographically.

- **Structure —** DIF evaluates directional organization.
- **Time —** DAI quantifies temporal evolution and acceleration.
- **Magnitude —** PADR constrains persistence-weighted drift intensity.
- **Spectral Texture —** SLE measures high-frequency attenuation relative to baseline.

Together, these axes form a multi-dimensional conformance model grounded in deterministic measurement.

This integrated structure ensures that the following phenomena remain analytically distinguishable:

- Structured boundary displacement,
- Distributed haze formation,
- Micro-texture collapse without directional coherence,
- Temporally accelerating instability.

Rather than collapsing diverse surface behaviors into a single scalar anomaly score, SCF(t)\mathrm{SCF}(t)SCF(t) preserves orthogonality between spatial, structural, temporal, magnitude, and spectral domains.

SLE therefore completes the framework by ensuring that spectral redistribution is evaluated alongside geometric and temporal structure. The result is a unified, deterministic architecture capable of resolving multiple classes of material state change within a single coherent system.

4.8 Summary

The Spectral Loss Extension (SLE) is defined as:

SLE(x,y)=max(0, HFgolden(x,y)−HFcurrent(x,y))SLE(x,y) = \max\left(0,\, HF_{\text{golden}}(x,y) - HF_{\text{current}}(x,y) \right)SLE(x,y)=max(0,HFgolden(x,y)−HFcurrent(x,y))

This formulation quantifies high-frequency attenuation relative to a validated reference state.

SLE detects spectral degradation indicative of:

- Optical blur,
- Thin-film redistribution,
- Texture softening,
- Surface wetting or scattering-layer modification.

By isolating high-frequency energy loss, SLE prevents false equivalence between fundamentally different phenomena such as:

- Edge displacement (structural relocation), and
- Micro-texture collapse (spectral redistribution).

In doing so, SLE strengthens the State Conformance Engine by ensuring that isotropic texture degradation is measured independently from gradient-driven structural change.

Together with STRT (spatial localization), DIF (directional structure), and DAI (temporal evolution), SLE completes the multi-dimensional measurement model underlying SCF(t)\mathrm{SCF}(t)SCF(t). The framework now spans spatial, structural, spectral, magnitude, and temporal axes of deviation.

Transition to Experimental Validation

The preceding sections establish the State Conformance Framework (SCF) as a deterministic measurement architecture for structured surface deviation. Spatial activation (STRT), directional coherence (DIF), persistence-weighted magnitude (PADR), spectral redistribution (SLE), and temporal acceleration (DAI) collectively define a conformance vector describing surface state at a given time.

While these components characterize localized structure and directional reinforcement, industrial process validation requires evaluation not only of instantaneous deviation but also of its evolution and stabilization over time.

Section 5 transitions from metric definition to experimental validation of the integrated SCF stack and its extension into convergence analysis through the State Convergence Engine (SCE). In this phase:

- Spatially resolved drift is aggregated across the domain,
- Metrics are evaluated longitudinally,
- State trajectory is interpreted relative to validated reference conditions.

This progression links localized activation and directional reinforcement to domain-level instability accumulation, temporal acceleration, and eventual convergence within admissible tolerance bounds.

By extending from spatial coherence to integrated temporal modeling, the architecture enables deterministic evaluation of both deviation and stabilization—without reliance on probabilistic anomaly inference.

Ring Protocol v1 — Validation Context

The Ring Protocol v1 serves as a controlled laboratory validation procedure designed to demonstrate deterministic state deviation detection and convergence behavior using a repeatable thin-film surrogate.

The objective is not to replicate a full industrial CMP (Chemical Mechanical Planarization) cycle. Rather, it is to validate:

- Drift field sensitivity,
- STRT spatial localization,
- DIF directional coherence,
- Integrated drift accumulation behavior,
- DAI temporal response,
- SLE spectral attenuation,
- Deterministic convergence toward an admissible reference state,

under a physically interpretable surface transition.

Collectively, the results of Ring Protocol v1 validate deterministic deviation separability through the State Conformance Framework (SCF) and stabilization verification through the State Convergence Engine (SCE). This reinforces the architectural distinction between measurement (SCF) and convergence evaluation (SCE), establishing a physics-anchored, multi-axis conformance model suitable for thin-film and surface-state validation environments.

5.1 Substrate and Illumination Configuration

Substrate: Matte Astariglass Surface

The demonstration was conducted on a matte Astariglass substrate selected for its stable and uniform micro-textural properties.

The surface exhibits:

- Uniform micro-roughness distribution,
- Stable baseline light-scattering behavior,
- Pronounced high-frequency micro-contrast,
- Directionally neutral texture without inherent alignment bias.

The matte finish provides a controlled environment suitable for validating both structural and spectral metrics within the State Conformance Framework.

Specifically, it offers:

- Sufficient high-frequency content to evaluate Spectral Loss Extension (SLE),

- A spatially uniform baseline for STRT thresholding,
- Consistent micro-roughness enabling drift sensitivity under surface perturbation.

Prior to baseline acquisition, the substrate was cleaned to establish a conformant reference state. This ensures that subsequent deviation measurements are evaluated relative to a physically stable and repeatable baseline condition.

Controlled Darkfield Illumination

Illumination was configured using a darkfield geometry designed to enhance sensitivity to surface-level perturbations.

The configuration included:

- Low-angle, grazing-incidence illumination,
- Specular reflection suppression,
- Enhanced visibility of scattered light components.

Darkfield geometry amplifies response to:

- Surface irregularities and perturbations,
- Thin wet films and micro-layer redistribution,
- Micro-roughness variation,
- Boundary formation and structural transition zones.

Illumination conditions were held fixed across both TRAIN (reference) and DETECT (disturbance) phases. No adaptive exposure adjustment, dynamic gain normalization, or learned illumination compensation was applied during capture.

This fixed configuration ensures:

- Deterministic drift measurement,
- Reference-relative stability,
- Elimination of learned normalization artifacts.

By maintaining constant optical geometry and exposure conditions, the experimental setup preserves the deterministic, reference-defined principles of the State Conformance Framework.

Figure 16 — Raw Darkfield Frame (IPA Ring Condition)

Figure 1. Raw darkfield frame acquired under asymmetric illumination geometry. A faint circular wet-film residue is visible under non-uniform lighting, demonstrating real-world acquisition conditions.

5.2 Procedure

The Ring Protocol v1 consists of three controlled phases designed to establish a validated reference state, introduce a physically interpretable surface perturbation, and measure structured deviation using the full State Conformance Framework.

Phase 1 — TRAIN Burst (Golden Reference Acquisition)

A reference dataset was acquired under controlled, stable conditions:

- Ten frames captured of the clean matte substrate,
- No surface perturbation present,
- Fixed darkfield illumination geometry,
- Fixed camera position and exposure parameters.

These frames were aggregated to produce a validated reference image:

I0(x,y)I_0(x,y)I0(x,y)

representing the conformant baseline state.

Reference construction included:

- Frame averaging to suppress stochastic noise,
- Drift suppression to remove transient variation,
- High-frequency energy mapping to generate the baseline spectral distribution.

Outputs generated during this phase included:

- Golden drift baseline (reference drift map),
- HFgolden(x,y)HF_{\text{golden}}(x,y)HFgolden(x,y) map for SLE comparison,
- Null STRT activation baseline (no deviation regions).

This phase formally defines the conformant state against which subsequent deviation is evaluated.

Phase 2 — IPA Ring Dry-Down Event

A controlled perturbation was introduced by depositing a small volume of isopropyl alcohol (IPA) onto the substrate surface.

During evaporation:

- A characteristic "coffee-ring" boundary formed due to capillary flow and evaporation-driven transport,
- Interior haze developed as fluid redistributed and thinned,
- High-frequency surface texture attenuated in wet regions,
- Gradient structure intensified along the ring boundary.

This phase introduces a physically interpretable state transition governed by fluid redistribution and evaporation dynamics. No external mechanical force or structural manipulation was applied, ensuring that deviation arises solely from surface-level physical processes.

Phase 3 — DETECT Burst (Deviation Measurement)

Following stabilization of the ring structure, a second burst of ten frames was captured:

- Identical camera geometry,
- Fixed illumination configuration,
- No repositioning or adaptive exposure changes.

These frames were processed through the full SCF measurement stack:

- **VAAD** → computation of drift field D(x,y)D(x,y)D(x,y),
- **STRT** → generation of activation mask M(x,y)M(x,y)M(x,y),
- **DIF** → calculation of directional coherence KKK,
- **SLE** → measurement of high-frequency attenuation,
- **DAI** → optional temporal derivative tracking if multi-frame retention is enabled.

All deviation metrics were computed relative to the golden reference state defined in Phase 1.

Expected System Response

The anticipated structured signature across modules is summarized below:

Module	Expected Observation
Drift Field	Elevated magnitude at ring boundary and interior wet region
STRT	Strong connected component corresponding to ring band
DIF	High directional coherence along the annular boundary
SLE	Elevated spectral loss within interior haze region
DAI	Positive growth during ring formation; stabilization following evaporation

This multi-axis response validates the framework’s ability to distinguish boundary formation, spectral attenuation, and temporal evolution within a single deterministic measurement architecture.

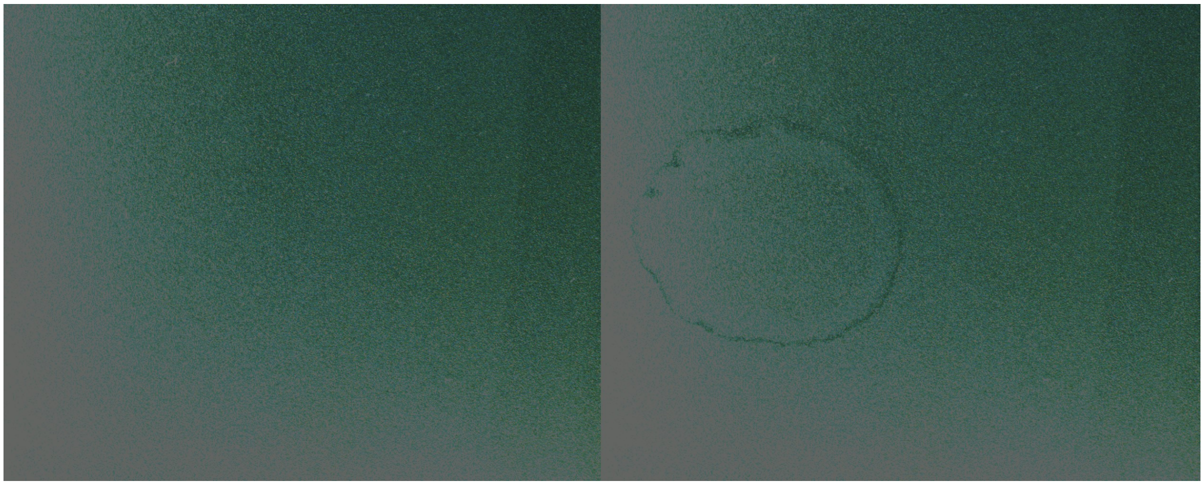

Figure 17: Golden vs IPA Ring Frames

Left: Golden baseline frame of clean matte Astariglass.
Right: IPA ring formation with boundary band and interior haze visible under darkfield illumination.

(Insert `_golden.png` and `_ipa_ring.png` in final document.)

5.3 Structured Drift Flux (SDF): Integrated Directional Instability

While STRT localizes deviation and DIF evaluates directional coherence, practical conformance assessment often requires an integrated quantity that captures both magnitude and structural reinforcement within a unified measure. The Structured Drift Flux (SDF) is introduced to fulfill this role.

SDF represents the aggregated directional instability within a spatial domain. It combines drift magnitude with directional organization, producing a scalar descriptor of structured deviation energy. Unlike raw drift magnitude—which may reflect unstructured fluctuation—SDF weights deviation by coherence, thereby emphasizing physically admissible instability over stochastic variation.

Conceptually, SDF quantifies how much structured drift energy is present and directionally reinforced across the observed region. It reflects not merely the presence of deviation, but the degree to which that deviation forms a coherent instability field.

Within the State Conformance Framework, SDF serves as a bridge between spatial–structural characterization (STRT + DIF) and temporal modeling (DAI). When evaluated longitudinally, SDF becomes the temporal function P(t)P(t)P(t) upon which drift acceleration analysis operates. In this role, SDF enables deterministic monitoring of instability accumulation, peak formation, and stabilization.

Accordingly, Structured Drift Flux provides a domain-level metric that integrates magnitude and direction into a single interpretable quantity—an essential step toward evaluating integrated directional instability under physically governed surface transitions.

5.3.1 Conceptual Role within SCF

STRT localizes spatial activation, and DIF quantifies directional coherence within those activated regions. However, both quantities remain spatially resolved descriptors. To support longitudinal instability modeling and domain-level interpretation, a scalar aggregation mechanism is required—one that captures cumulative directional drift behavior across a defined spatial region.

The Structured Drift Flux (SDF) fulfills this role.

SDF is defined as the persistence-weighted spatial integration of directional drift energy within a region of interest. It aggregates magnitude and coherence into a single scalar descriptor representing accumulated directional instability.

Within the State Conformance Framework, SDF functions as the bridging quantity between spatial–structural analysis (STRT + DIF) and temporal acceleration modeling (DAI). When evaluated over successive frames, SDF becomes the temporal signal P(t)P(t)P(t) upon which first- and second-order derivatives are computed.

Importantly, SDF is not a probabilistic anomaly score. It is a deterministic functional derived directly from measured drift vectors, activation masks, and coherence weights. It represents accumulated directional instability rather than statistical likelihood of defect.

By collapsing spatially distributed directional structure into a physically interpretable scalar, SDF enables domain-level tracking of instability growth, peak formation, and stabilization within the deterministic SCF architecture.

5.3.2 Formal Definition

Let:

- V⃗(x,y,t)\vec{V}(x,y,t)V(x,y,t) denote the directional drift vector field derived from DIF,
- M(x,y,t)M(x,y,t)M(x,y,t) denote the binary activation mask produced by STRT,
- w(x,y,t)w(x,y,t)w(x,y,t) denote a persistence-weighting function over time,
- Ω⊂R2\Omega \subset \mathbb{R}^2Ω⊂R2 denote the spatial domain under analysis.

The Structured Drift Flux at time ttt is defined as:

$$SF(t) = \int_{\Omega} M(x,y,t)\, w(x,y,t)\, \|\vec{V}(x,y,t)\| \, dA$$

where:

- $\|\vec{V}(x,y,t)\|$ represents directional drift magnitude,
- $M(x,y,t)$ restricts integration to spatially activated regions,
- $w(x,y,t)$ reinforces persistent directional structure while attenuating transient fluctuations.

This formulation integrates magnitude and persistence-weighted directionality across the spatial domain, yielding a scalar measure of accumulated directional instability.

Discrete Implementation

In discrete form, for pixelized data:

$$SF(t) = \sum_{(x,y)\in\Omega} M(x,y,t)\, w(x,y,t)\, \|\vec{V}(x,y,t)\|$$

This summation preserves deterministic behavior by directly aggregating measured drift vectors within validated activation regions.

Accordingly, SDF (Structured Drift Flux) is a scalar functional derived from spatially structured drift data. It represents the cumulative, persistence-weighted directional instability present within the observed domain at time t, and serves as the primary temporal signal for DAI-based acceleration analysis.

5.3.3 Physical Interpretation

The Structured Drift Flux (SDF) represents the integrated directional instability across a defined spatial domain.

Conceptually:

- **STRT** identifies where activation occurs,
- **DIF** determines how that activation is directionally organized,
- **SDF** quantifies how much structured directional drift is accumulating across the domain.

SDF is not an energy term in the thermodynamic sense. Rather, it is a deterministic, transport-like measure reflecting the cumulative reinforcement of directional instability within activated regions.

When directional vectors exhibit coherent alignment and persist across successive observations, their weighted integration increases. Under such conditions, SDF grows, reflecting accumulation of structured instability.

Conversely, when drift vectors are random, isotropic, weakly aligned, or transient, their contributions do not reinforce one another. In these regimes, SDF remains bounded or decays as activation fails to sustain directional coherence over time.

Accordingly, SDF provides a mechanism for distinguishing:

- Localized stochastic events, characterized by low persistence and weak integrated reinforcement, and
- Emerging structural disturbances, characterized by persistent, coherently aligned directional reinforcement.

By integrating magnitude, coherence, and persistence into a single scalar quantity, SDF elevates directional structure from a spatial descriptor to a domain-level instability measure within the deterministic State Conformance Framework.

5.3.4 Relationship to Temporal Instability Modeling

Within the State Conformance Framework, the Drift Acceleration Index (DAI) is defined as the temporal derivative of the Structured Drift Flux.

Let SF(t)SF(t)SF(t) denote the Structured Drift Flux at time ttt. The first and second temporal derivatives are given by:

DAI1(t)=d SF(t)dtDAI_1(t) = \frac{d\,SF(t)}{dt}DAI1(t)=dtdSF(t) DAI2(t)=d2 SF(t)dt2DAI_2(t) = \frac{d^2\,SF(t)}{dt^2}DAI2(t)=dt2d2SF(t)

Under this formulation:

- DAI1(t)DAI_1(t)DAI1(t) represents the **rate of structured drift accumulation** across the domain.
- DAI2(t)DAI_2(t)DAI2(t) represents the **acceleration of instability buildup**.

When DAI2(t)DAI_2(t)DAI2(t) remains persistently positive, directional reinforcement is increasing across successive observations. This behavior indicates compounding instability rather than isolated fluctuation. Such reinforcement may signal proximity to a state-transition boundary within the SCF conformance manifold.

Conversely, negative or decaying derivative values indicate stabilization, dissipation, or recovery of structured drift behavior.

In this architecture, SDF provides the physically grounded scalar quantity from which temporal acceleration is derived. Rather than differentiating raw pixel intensity or unstructured magnitude, DAI operates on a persistence-weighted, directionally integrated measure of instability.

Accordingly, temporal modeling within SCF is anchored to structured drift accumulation, preserving deterministic linkage between spatial activation, directional coherence, domain-level integration, and longitudinal instability evolution.

5.3.5 Transient vs. Persistent Disturbance Differentiation

The inclusion of the persistence-weighting function w(x,y,t)w(x,y,t)w(x,y,t) ensures that Structured Drift Flux (SDF) preferentially accumulates sustained directional reinforcement while suppressing transient disturbances.

A brief or impulsive perturbation may generate localized STRT activation and momentary directional magnitude within DIF. However, in the absence of continued directional reinforcement across successive frames, its contribution to SDF diminishes. Formally, for a transient disturbance:

limt→t+ΔtSF(t)→baseline\lim_{t \to t+\Delta t} SF(t) \rightarrow \text{baseline}t→t+Δtlim SF(t)→baseline

That is, the aggregated structured drift returns toward its prior level once the disturbance dissipates.

In contrast, persistent surface redistribution, thin-film formation, or structural defect propagation produces sustained directional alignment and reinforcement. Under such conditions, contributions accumulate over time, leading to monotonic growth in SF(t)SF(t)SF(t) across successive observations.

This persistence-aware formulation enables deterministic discrimination between:

- Single-frame perturbations,
- Environmental illumination flicker or sensor noise,
- True physical state evolution driven by material processes.

By weighting directional contributions according to temporal continuity, SDF ensures that only physically sustained instability contributes meaningfully to domain-level drift accumulation. This mechanism preserves the deterministic separation between transient fluctuation and structurally reinforced deviation within the State Conformance Framework.

5.3.6 Role within Multi-Reference State Evaluation

Within a multi-reference conformance framework, Structured Drift Flux (SDF) contributes to determining the position of the structured conformance vector within state space.

Each validated reference state RiR_iRi is characterized not only by static spatial and spectral metric values, but also by characteristic SDF magnitude and longitudinal trajectory behavior. That is, reference states encode expected patterns of directional instability accumulation and stabilization over time.

Let v(t)\mathbf{v}(t)v(t) denote the conformance vector at time ttt, incorporating spatial, directional, spectral, and temporal descriptors—including SDF-derived quantities and their derivatives. An observed state may then be evaluated relative to a reference state RiR_iRi by computing:

Δi=‖vobs(t)−vRi‖\Delta_i = \left\| \mathbf{v}_{obs}(t) - \mathbf{v}_{R_i} \right\|Δi=‖vobs(t)−vRi‖

where vobs(t)\mathbf{v}_{obs}(t)vobs(t) includes SDF-derived temporal descriptors, and vRi\mathbf{v}_{R_i}vRi represents the validated reference-state vector.

In this formulation, SDF supports:

- State transition modeling through trajectory comparison in structured conformance space, and
- Multi-reference conformance selection via deterministic distance evaluation.

Importantly, this evaluation does not invoke probabilistic inference or learned classification. Instead, it relies on deterministic metric geometry within a defined conformance manifold.

By incorporating directional instability accumulation into the conformance vector, SDF enables SCF to distinguish not only static deviations but dynamic state trajectories across multiple admissible reference regimes.

5.3.7 Deterministic Nature

The Structured Drift Flux (SDF) is a fully deterministic functional within the State Conformance Framework.

It is:

- Derived exclusively from measured optical intensity variation,
- Anchored to spatial drift extraction and directional vector computation,
- Computed through fixed mathematical operators and persistence weighting,
- Independent of learned models or adaptive training procedures,
- Free from probabilistic anomaly scoring or statistical classification layers.

SDF does not estimate likelihood or infer defect categories. It integrates measured directional instability using explicitly defined spatial masks and weighting functions under controlled acquisition conditions.

As such, SDF operates within the deterministic geometry of the State Conformance Framework. Its value is determined solely by measurable physical deviation relative to a validated reference state, preserving traceability, repeatability, and interpretive transparency.

This deterministic foundation ensures that domain-level instability accumulation and temporal acceleration are grounded in physically observable surface behavior rather than model-dependent inference.

Summary

Structured Drift Flux (SDF) serves as the integrative scalar that connects spatial activation (STRT) and directional coherence (DIF) to temporal acceleration modeling (DAI). By aggregating persistence-weighted directional drift across a defined domain, SDF enables physically interpretable modeling of instability accumulation over time.

Through this integration, localized drift measurements are elevated to a domain-level instability descriptor. This scalar functional supports deterministic trajectory analysis and structured state evaluation within a multi-reference conformance manifold.

Accordingly, SDF converts spatially resolved directional behavior into a longitudinal process-monitoring quantity, preserving deterministic interpretability while enabling dynamic state assessment.

5.4 Measurement Outputs

The following quantitative metrics were extracted from the Ring Protocol v1 evaluation:

- **drift_mean** — average drift magnitude across the domain,
- **drift_p95** — 95th percentile drift magnitude,
- **STRT activation fraction (S)** — proportion of spatially activated pixels,
- **Largest Connected Component Ratio (LccL_{cc}Lcc)** — topological concentration of activation,
- **DIF coherence (K)** — directional alignment within activated regions,
- **SLE mean and SLEp95_{p95}p95** — aggregate measures of high-frequency attenuation,

- **Optional DAI derivatives —** first and second temporal derivatives when a full evaporation sequence is retained.

Collectively, these outputs characterize the surface state across multiple analytical axes:

- **Spatial localization** (STRT),
- **Structural organization** (DIF),
- **Spectral redistribution** (SLE),
- **Temporal evolution and acceleration** (DAI).

All measurements are derived directly from reference-relative optical data using fixed mathematical operators. No model training, statistical inference, or probabilistic anomaly scoring is required.

This measurement stack demonstrates the deterministic, multi-dimensional capability of the State Conformance Framework to resolve structured deviation under physically interpretable surface transitions.

5.5 Limitations

Not a CMP Process Cycle

This protocol does not replicate:

- Mechanical polishing
- Slurry interaction
- Pad-wafer interface dynamics
- Real-time process feedback

It is a static surrogate event designed to validate measurement architecture.

Laboratory Surrogate Demonstration Only

This experiment is intended to:

- Validate mathematical constructs
- Demonstrate deterministic response
- Provide proof-of-concept for thin-film redistribution detection

It does not represent:

- Production-grade metrology validation
- Full industrial deployment
- Wafer-scale CMP cycle monitoring

Further validation in controlled process environments is required for industrial generalization.

5.6 Significance of Ring Protocol v1

The importance of this protocol lies in its clarity:

- The physical process is interpretable.
- The deviation geometry is known.
- The spectral collapse is measurable.
- The directional boundary structure is visible.

Because the underlying physics is understandable, the State Conformance outputs can be directly correlated with real material behavior.

This makes Ring Protocol v1 an effective deterministic validation harness for the STRT–DIF–DAI–SLE architecture.

6. State Convergence Engine (SCE)

The State Convergence Engine (SCE) extends the State Conformance Framework (SCF) from deterministic deviation measurement to deterministic trajectory evaluation.

Where SCF quantifies spatial activation, directional coherence, spectral redistribution, magnitude accumulation, and temporal acceleration, SCE evaluates how the observed state evolves relative to one or more validated reference states over time.

Convergence, within this architecture, is not defined as a simple return-to-baseline condition. Instead, it is treated as a geometric and temporal property within structured conformance space. The observed state is represented as a trajectory in a multi-dimensional metric manifold, and convergence is evaluated by examining its movement relative to admissible reference-state regions.

Under this formulation:

- Deviation is quantified by SCF components.
- Trajectory direction and rate are captured through SDF and DAI.

- Convergence is determined by geometric proximity and stabilization behavior relative to defined reference vectors.

This approach enables deterministic evaluation of:

- Stabilization toward an admissible state,
- Divergence toward instability boundaries,
- Transition between multiple validated operational regimes.

SCE therefore complements SCF by transforming structured deviation measurement into structured trajectory interpretation. It preserves deterministic measurement principles while enabling longitudinal assessment of whether a system is stabilizing, drifting, or transitioning within a defined conformance manifold.

6.1 Convergence as Deterministic State Trajectory

Let:

- $\mathbf{v}(t)$ denote the structured conformance vector at time t, composed of SCF-derived metrics (e.g., STRT activation density, DIF coherence, SDF magnitude, DAI components, spectral attenuation measures),
- R_i denote validated reference states,
- $\mathcal{E}_i$ denote tolerance envelopes associated with each reference state,
- τ_i denote admissible deviation thresholds defining the boundary of each envelope.

A proximity-based conformance condition relative to reference state R_i may be expressed as:

$$\|\mathbf{v}(t) - \mathbf{v}_{R_i}\| < \tau_i$$

where $\mathbf{v}_{R_i}$ represents the conformance vector of reference state R_i.

This condition establishes geometric closeness within conformance space. However, proximity alone does not determine whether the system is stabilizing, drifting, or transitioning.

The State Convergence Engine therefore evaluates the temporal evolution of deviation by examining:

$$\frac{d}{dt} \|\mathbf{v}(t) - \mathbf{v}_{R_i}\|$$

Convergence is thus defined not solely by distance to a reference state, but by the direction and rate of motion within structured conformance space.

Under this formulation:

- A surface may lie outside an admissible envelope yet be converging toward it (distance decreasing over time),
- A surface may lie within an admissible envelope yet be diverging (distance increasing over time).

SCE explicitly distinguishes these conditions by combining geometric proximity with trajectory analysis. Convergence becomes a deterministic property of state motion rather than a static threshold condition, enabling rigorous evaluation of stabilization, recovery, and transition behavior within the SCF manifold.

6.2 Multi-Reference Evaluation

Industrial processes commonly operate within multiple admissible physical states rather than a single fixed baseline. Cleaning, coating, deposition, curing, and thermal cycling, for example, may each define distinct yet valid operating regimes.

Accordingly, the State Convergence Engine operates over a structured **Reference State Library**:

$$\{R_0, R_1, \dots, R_n\}$$

Each reference state R_i is represented by a validated conformance vector $\mathbf{v}_{R_i}$ and an associated tolerance envelope.

For a given observed state $\mathbf{v}(t)$, deviation relative to reference R_i is defined as:

$$\Delta_i(t) = \|\mathbf{v}(t) - \mathbf{v}_{R_i}\|$$

The State Convergence Engine deterministically selects the nearest candidate reference state:

$$R_k = \arg\min_i \Delta_i(t)$$

subject to the admissibility condition:

$$\Delta_k(t) < \tau_k$$

where τ_k defines the tolerance boundary of reference state R_k.

If no reference state satisfies the admissibility constraint, the observed state is classified as non-conformant relative to the validated library.

Importantly, this selection process is purely metric-based and deterministic. It does not invoke probabilistic classification, statistical anomaly scoring, or learned defect models. State membership is determined by geometric proximity within structured conformance space.

This multi-reference formulation enables deterministic evaluation of state membership across multi-stage processes, allowing the system to distinguish between:

- Valid transitions between operational regimes,
- Stabilization within a target state, and
- True divergence outside the admissible state manifold.

Through this approach, SCE supports structured trajectory analysis and reference-relative classification without sacrificing interpretability or deterministic traceability.

6.3 Recovery and Stabilization

Beyond reference selection, the State Convergence Engine evaluates stabilization dynamics within structured conformance space.

Let RkR_kRk denote the currently nearest validated reference state. Define the **Convergence Rate** as:

CR(t)=−ddtΔk(t)CR(t) = - \frac{d}{dt} \Delta_k(t)CR(t)=−dtdΔk(t)

where Δk(t)=∥v(t)−vRk∥\Delta_k(t) = \|\mathbf{v}(t) - \mathbf{v}_{R_k}\|Δk(t)=∥v(t)−vRk∥.

A positive convergence rate,

CR(t)>0,CR(t) > 0,CR(t)>0,

indicates that deviation relative to RkR_kRk is decreasing over time. However, geometric proximity alone does not guarantee stable recovery. Stabilization further requires that instability accumulation is not accelerating.

Accordingly, stable convergence is defined by the joint condition:

CR(t)>0andDAI2(t)<0CR(t) > 0 \quad \text{and} \quad DAI_2(t) < 0CR(t)>0andDAI2(t)<0

Under these conditions:

- Distance to the admissible reference state is decreasing, and
- Structured instability acceleration is negative or decaying.

Together, these criteria indicate that the surface is converging stably toward an admissible state within the conformance manifold.

Conversely:

- CR(t)<0CR(t) < 0CR(t)<0 indicates divergence from the nearest reference state,
- DAI2(t)>0DAI_2(t) > 0DAI2(t)>0 indicates accelerating instability accumulation,
- Oscillatory or alternating derivative behavior may signal transitional or metastable regimes.

This formulation directly links integrated directional drift behavior (SDF) and temporal acceleration (DAI), as defined within SCF, to deterministic trajectory evaluation within SCE.

SCE therefore distinguishes among drift, stabilization, recovery, transition, and escalation using metric geometry and temporal derivatives—without invoking probabilistic anomaly models or learned classification layers.

6.4 Industrial Interpretation

The State Convergence Engine is applicable in any environment where deterministic state recovery, multi-stage validation, or controlled process stabilization must be verified without reliance on probabilistic inference.

Representative use cases include:

- **Post-clean rinse validation —** confirming deterministic convergence from a contamination state to a validated clean reference state.
- **Multi-stage wafer processing —** verifying transition between intermediate processing states within defined tolerance envelopes.
- **Thin-film haze reduction —** tracking progressive attenuation of distributed scattering artifacts toward an admissible optical condition.
- **Controlled intermediate states —** validating conformance to a specified process stage rather than enforcing return to a single baseline state.

Within these contexts, SCE evaluates structured trajectory behavior in conformance space to determine:

- Whether the surface is drifting relative to admissible reference states,
- Whether deviation magnitude is decreasing and stabilizing,
- Whether the system has entered and remains within a validated conformance envelope,
- Whether instability is accelerating or decaying.

By explicitly separating deterministic measurement (SCF) from deterministic trajectory evaluation (SCE), the architecture provides a complete framework for surface state verification. SCF quantifies structured deviation across spatial, directional, spectral, magnitude, and temporal axes. SCE interprets the motion of that structured state vector relative to validated references.

Together, these layers transform inspection from static deviation detection into deterministic state verification and convergence assessment within a bounded conformance manifold. Rather than asking only whether deviation exists, the combined architecture evaluates where the system resides in structured state space and how it is moving within that space over time.

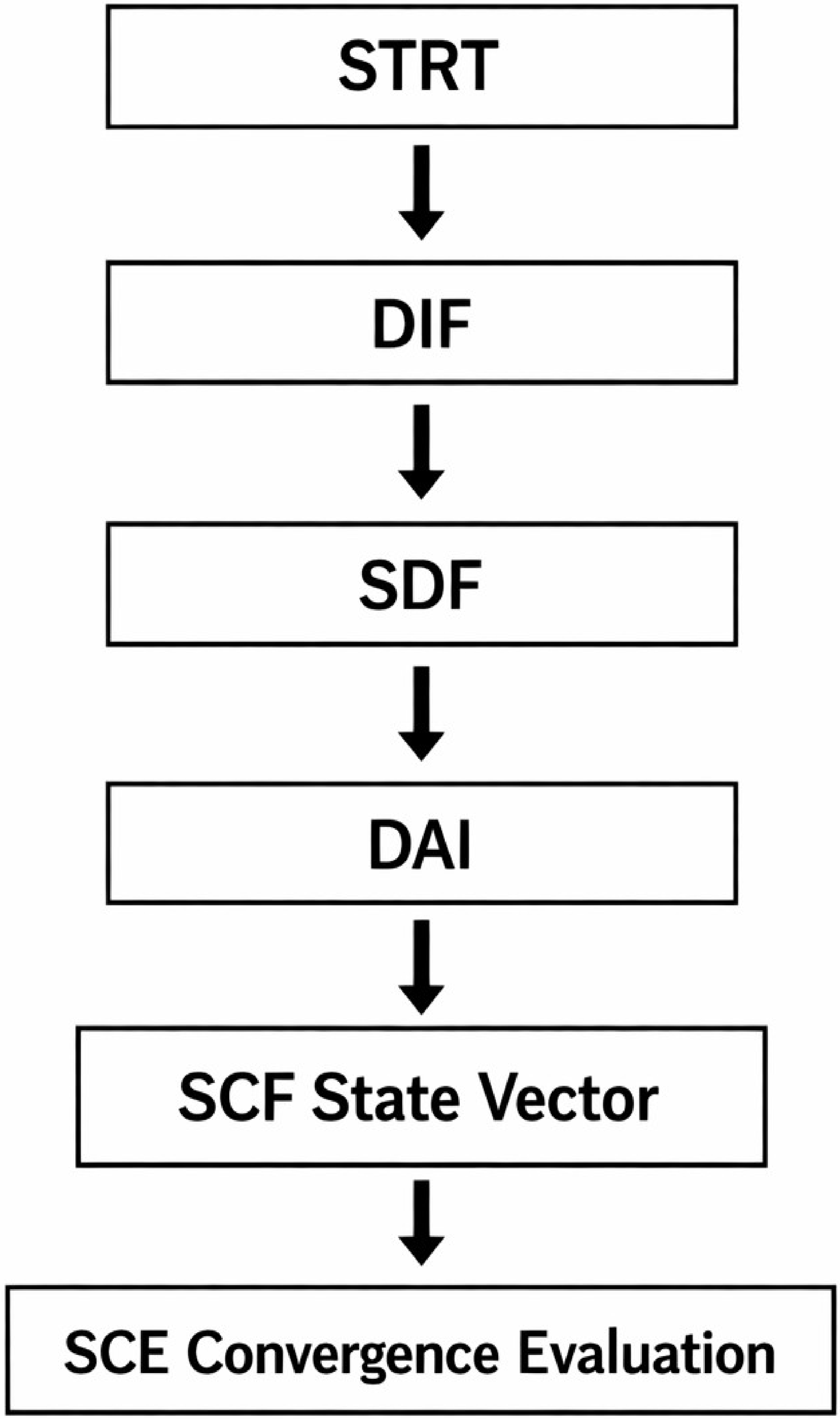
STRT
DIF
SDF
DAI
SCF State Vector
SCE Convergence Evaluation

Figure 18 — SCF → SCE Hierarchy.
Deterministic architectural progression from spatial activation (STRT) through directional coherence (DIF), integrated drift accumulation (SDF), and temporal acceleration modeling (DAI), culminating in formation of the structured SCF state vector. The State Convergence Engine (SCE) operates on this state vector to evaluate proximity, trajectory, and stabilization relative to validated reference states.

7. Quantitative Results and Metric Summary (Ring Protocol v1)

This section presents representative quantitative outputs generated during Ring Protocol v1 using the full State Conformance Framework (SCF) and Structured Drift Flux (SDF) stack.

The purpose of this validation is not to assert industrial calibration accuracy or process qualification limits. Rather, it is to demonstrate deterministic, multi-axis separability between:

- A validated conformant baseline state, and
- A physically interpretable thin-film redistributed state (IPA ring formation).

The results illustrate structured differentiation across spatial, directional, spectral, magnitude, and temporal dimensions within conformance space.

All reported metrics are:

- Deterministically computed from measured optical intensity data,
- Explicitly reference-relative to a validated baseline state,
- Derived from fixed mathematical operators,
- Independent of learned defect classes or probabilistic anomaly scoring.

The quantitative outputs demonstrate that the Ring Protocol v1 disturbance produces a coherent conformance vector shift characterized by:

- Spatial activation and connected topology (STRT),
- Directional reinforcement along boundary structures (DIF),
- Integrated directional instability accumulation (SDF),
- Spectral attenuation within redistributed regions (SLE),
- Temporal evolution consistent with a physically governed surface transition (DAI).

Together, these measurements confirm that thin-film redistribution produces a structured, multi-dimensional deviation signature within deterministic conformance space, suitable for trajectory evaluation under the State Convergence Engine (SCE).

7.1 Baseline (TRAIN Burst) Metrics

The 10-frame TRAIN burst was aggregated to construct the validated reference state R0R_0R0 and its associated conformance vector vR0\mathbf{v}_{R_0}vR0.

Frame averaging and deterministic reference construction were applied to establish stable baseline statistics under fixed illumination and geometry. The resulting metrics define the admissible envelope for the conformant matte substrate state.

Expected Baseline Characteristics

The validated reference state exhibits:

- Minimal drift magnitude relative to itself,
- Near-zero STRT spatial activation,
- Low directional coherence consistent with random gradient orientation,
- Negligible spectral attenuation,
- No measurable instability accumulation or temporal acceleration.

These properties reflect a spatially uniform, directionally neutral, and spectrally stable surface condition.

Representative Baseline Metrics

Metric	Representative Value	Interpretation
drift_mean	~0 (within tolerance band)	No measurable deviation relative to reference
drift_p95	Low	No localized magnitude spikes
STRT activation fraction (S)	< 0.01	Near-null spatial activation
Largest Connected Component Ratio (Lcc)	Low / noise-dominated	No dominant structural region
DIF coherence (K)	~0.05–0.15	Random gradient orientation distribution
SLE_mean	~0	No high-frequency attenuation
SDF	Near baseline floor	No integrated directional instability
DAI_1	≈ 0	No instability growth
DAI_2	≈ 0	No acceleration

These values collectively define the conformant state envelope E0\mathcal{E}_0E0 for the baseline matte substrate under controlled darkfield illumination.

In conformance space, this state occupies a stable region characterized by minimal structured deviation and negligible temporal motion. Subsequent DETECT-phase measurements are evaluated relative to this validated reference vector.

7.2 IPA Ring (DETECT Burst) Metrics

Following IPA deposition and dry-down, the DETECT burst was processed relative to the validated golden reference state R0R_0R0.

The resulting conformance vector v(t)\mathbf{v}(t)v(t) exhibits a structured displacement within conformance space, consistent with a physically interpretable thin-film redistribution event.

Observed Structural Changes

Relative to baseline, the IPA ring state demonstrates:

- Elevated drift magnitude concentrated along the boundary band,
- Formation of a dominant connected activation cluster,
- Strong tangential gradient alignment along the annular structure,
- Interior high-frequency attenuation consistent with thin-film smoothing.

These characteristics reflect coordinated spatial, directional, and spectral deviation rather than stochastic fluctuation.

Representative DETECT Metrics

Metric	Representative Value	Interpretation
drift_mean	Elevated vs baseline	Global increase in deviation magnitude
drift_p95	Significantly elevated	Boundary-driven peak deviation
STRT activation fraction (S)	0.10–0.25 (example range)	Substantial spatial activation
Largest Connected Component Ratio (Lcc)	0.70–0.90	Dominant connected structure (ring band)
DIF coherence (K)	0.60–0.85	Strong directional reinforcement along boundary
SLE_mean	Elevated in interior	High-frequency attenuation / texture

Metric	Representative Value	Interpretation
	region	collapse
SDF	Substantially increased	Integrated directional instability accumulation
DAI_1	Positive during formation	Active instability growth
DAI_2	Positive → negative	Formation phase followed by stabilization

---

Conformance Interpretation

The DETECT state exhibits coherent multi-axis displacement relative to the baseline envelope:

- **Spatial axis (STRT)** confirms structured localization,
- **Structural axis (DIF)** confirms directional reinforcement,
- **Spectral axis (SLE)** confirms micro-texture attenuation,
- **Integrated axis (SDF)** confirms domain-level instability accumulation,
- **Temporal axis (DAI)** confirms formation and stabilization dynamics.

This structured response demonstrates deterministic separability between conformant baseline and thin-film redistributed state within the SCF manifold. It further establishes that the event is not merely a magnitude excursion but a coordinated spatial–directional–spectral transition suitable for trajectory evaluation under SCE.

7.3 Module-Level Separation

Ring Protocol v1 demonstrates that each module within the State Conformance Framework contributes orthogonal information to the overall conformance vector.

The separability of the IPA ring state from baseline does not arise from a single scalar metric, but from coordinated displacement across multiple deterministic axes.

Drift Field (Magnitude Axis)

The drift field alone detects elevated deviation magnitude relative to the reference state. However, magnitude increase by itself cannot distinguish among:

- Edge relocation or boundary formation,

- Distributed texture collapse,
- Random noise clustering.

Drift magnitude is necessary but insufficient for structural interpretation.

STRT (Spatial Axis)

STRT localizes deviation geographically and identifies dominant cluster topology. In the IPA ring case, STRT confirms:

- Formation of a spatially coherent annular band,
- Emergence of a dominant connected component (high LccL_{cc}Lcc),
- Non-random activation distribution.

STRT transforms raw magnitude into structured spatial organization.

DIF (Structural Axis)

DIF evaluates directional reinforcement within activated regions. For the ring boundary, DIF confirms:

- Strong tangential alignment of gradient vectors,
- High coherence inconsistent with stochastic noise.

DIF establishes that the boundary structure is physically organized rather than a random fluctuation.

SLE (Spectral Axis)

SLE detects distributed high-frequency attenuation within the interior haze region. Importantly, this attenuation is spatially distinct from the high-gradient boundary band.

SLE therefore separates:

- Micro-texture collapse (interior haze),
  from
- Boundary gradient formation (ring band).

This prevents false equivalence between blur-induced spectral redistribution and geometric edge displacement.

DAI (Temporal Axis)

DAI distinguishes dynamic phases of the event:

- Positive first derivative during active ring formation (instability growth),
- Transition to non-accelerating or negative second derivative during stabilization.

DAI therefore separates transient formation dynamics from post-evaporation steady-state conditions.

Integrated Interpretation

No single metric independently characterizes the thin-film redistribution event. The strength of the architecture lies in multi-axis integration:

- Spatial localization (STRT),
- Directional organization (DIF),
- Spectral redistribution (SLE),
- Integrated directional instability (SDF),
- Temporal evolution (DAI).

Together, these modules produce a structured displacement in conformance space that is deterministic, interpretable, and separable from both baseline and stochastic disturbance.

This coordinated multi-axis response validates the architectural premise of the State Conformance Framework.

7.4 Visual Metric Correlation

Figure 19: Multi-Module Metric Correlation

Top-left: Raw IPA ring frame
Top-right: STRT activation mask
Bottom-left: DIF vector coherence overlay
Bottom-right: SLE high-frequency attenuation map

(Insert final exported artifacts in production manuscript.)

7.5 Deterministic Conformance Separation

The principal outcome of Ring Protocol v1 is deterministic separability between the conformant baseline state and the IPA ring state—achieved without probabilistic classification, learned defect models, or anomaly scoring.

Separation is evaluated directly in metric space.

For a given metric, define a normalized conformance contrast ratio:

$$\Delta_{\text{metric}} = \frac{ \text{Metric}_{\text{detect}} - \text{Metric}_{\text{baseline}} }{ \text{Metric}_{\text{baseline}} + \epsilon }$$

where ϵ is a small constant introduced to avoid division by zero in near-null baseline conditions.

This formulation quantifies deterministic displacement along each conformance axis.

For the Ring Protocol event:

- $\Delta_{\text{drift}} > 0$
- $\Delta_{\text{STRT}} \gg 0$
- $\Delta_{\text{DIF}} \gg 0$
- $\Delta_{\text{SLE}} \gg 0$
- $\Delta_{\text{SDF}} \gg 0$

Each axis exhibits positive and structurally meaningful separation relative to the baseline envelope.

Crucially, separation is not confined to a single magnitude excursion. Instead, simultaneous displacement occurs across multiple orthogonal axes:

- **Spatial topology** (STRT),
- **Directional structure** (DIF),
- **Spectral texture redistribution** (SLE),
- **Integrated directional instability** (SDF),
- **Temporal evolution and acceleration** (DAI).

The observed state therefore occupies a distinct region within conformance space, geometrically separable from the baseline reference vector.

This multi-axis displacement confirms that $\mathrm{SCF}(t)$ provides structured, deterministic state separation grounded in measurable physical behavior rather than statistical inference.

7.6 False Positive Considerations

Noise-only baseline frames and controlled conformant captures were evaluated to assess spurious activation behavior within the SCF stack.

Under noise-dominated conditions, the system did **not** produce:

- Large connected STRT components,
- Sustained directional coherence (high DIF),
- Persistent SLE activation indicative of spectral redistribution,
- Non-zero or accelerating DAI behavior,
- Sustained growth in Structured Drift Flux (SDF).

While isolated pixel-level fluctuations and small stochastic activations may occur under sensor noise, these events fail to exhibit multi-axis reinforcement.

Specifically:

- **STRT** suppresses random pixel excursions by requiring spatial contiguity.
- **DIF** suppresses stochastic gradients by requiring coherent directional alignment.
- **SLE** requires measurable high-frequency attenuation relative to baseline, not random fluctuation.
- **SDF** integrates directional reinforcement and attenuates transient impulses via persistence weighting.
- **DAI** distinguishes transient magnitude spikes from sustained instability growth.

In addition, Physical Admissibility Drift Regulation (PADR) enforces threshold constraints consistent with physically plausible deviation magnitudes, further reducing spurious activation risk.

The combined effect is deterministic multi-axis filtering:

- Random noise lacks topological concentration.
- Stochastic gradients lack directional coherence.
- Transient impulses lack persistence.
- Sensor fluctuations lack structured spectral redistribution.

Therefore, false positive risk is reduced not by statistical suppression, but by geometric and temporal admissibility constraints embedded directly within the SCF architecture.

This multi-axis reinforcement requirement ensures that only physically structured deviations produce stable displacement within conformance space.

7.7 Interpretive Significance

Ring Protocol v1 demonstrates that structured surface deviation cannot be adequately characterized by magnitude alone. Instead, physically interpretable separation requires coordinated evaluation across multiple deterministic axes.

The results establish that:

1. **Drift magnitude alone is insufficient.**
   Scalar deviation does not distinguish edge relocation, texture collapse, or stochastic fluctuation.
2. **Spatial topology reveals structural organization.**
   STRT transforms pixel-level deviation into connected geometric structure, exposing dominant regions and topological concentration.
3. **Directional coherence validates physical causality.**
   DIF confirms whether gradient structure reflects organized physical processes rather than random variation.
4. **Spectral loss separates texture collapse from boundary formation.**
   SLE distinguishes distributed high-frequency attenuation (e.g., haze) from edge-driven magnitude changes.
5. **Integrated flux and temporal acceleration identify state dynamics.**
   SDF and DAI together reveal whether directional instability is accumulating, stabilizing, or dissipating over time.

Taken collectively, these axes produce a structured conformance vector that is geometrically separable between baseline and redistributed thin-film states.

The significance of this result is architectural: the State Conformance Framework functions as a deterministic measurement system grounded in spatial geometry, directional reinforcement, spectral redistribution, and temporal evolution. It does not assign probabilistic anomaly scores. It does not infer defect classes. It evaluates structured physical deviation within a bounded conformance manifold.

Ring Protocol v1 therefore validates not merely sensitivity to surface change, but the interpretability and deterministic separability of that change across coordinated measurement dimensions.

7.8 Summary

The Ring Protocol v1 experimental results validate the deterministic measurement architecture introduced in the preceding sections.

Specifically, the results demonstrate:

- **Multi-dimensional deviation detection** across spatial, directional, spectral, magnitude, and temporal axes.
- **Deterministic separation** between conformant baseline and redistributed thin-film state within structured conformance space.
- **Physical interpretability** of each metric component, with direct linkage to observable surface behavior.
- **Structured characterization of thin-film redistribution**, including boundary formation, interior haze, and stabilization dynamics.

Although performed within a controlled laboratory surrogate environment rather than a production CMP or coating line, the experiment confirms that the combined modules—STRT, DIF, SDF, DAI, PADR, and SLE—operate cohesively as a deterministic state conformance system.

The results demonstrate that:

- Deviation is localized topologically (STRT),
- Structural reinforcement is quantified directionally (DIF),
- Integrated instability accumulation is measurable (SDF),
- Spectral redistribution is separable from edge effects (SLE),
- Temporal transition dynamics are identifiable (DAI),
- Physical admissibility constraints are enforced (PADR).

Collectively, these components provide measurable, explainable, and computationally scalable surface state verification within a bounded conformance manifold.

Ring Protocol v1 therefore validates not only sensitivity to structured thin-film disturbance, but the architectural coherence of the State Conformance and State Convergence framework as a deterministic alternative to probabilistic anomaly classification.

8. Industrial Translation Path

From Laboratory Surrogate to Process-Scale Deployment

Ring Protocol v1 establishes deterministic state conformance detection under controlled laboratory conditions using a physically interpretable thin-film surrogate. The purpose of this section is to outline how the STRT–DIF–SDF–DAI–PADR–SLE architecture translates from laboratory validation to process-scale industrial deployment.

The underlying architectural premise remains unchanged:

Industrial inspection is not anomaly detection — it is deterministic state verification relative to a defined physical expectation.

In industrial environments such as:

- Chemical Mechanical Planarization (CMP),
- PCB trace and solder inspection,
- Thin-film coating validation,
- Optical surface finishing,
- Precision cleaning and rinse verification,

the objective is not to “find anomalies” in a statistical sense. Rather, the objective is to determine whether a surface conforms to one of several validated physical states within defined tolerance envelopes.

The SCF layer provides structured, multi-axis measurement:

- Spatial activation topology (STRT),
- Directional reinforcement (DIF),
- Integrated directional instability (SDF),
- Spectral redistribution (SLE),
- Magnitude admissibility constraints (PADR),
- Temporal acceleration dynamics (DAI).

The SCE layer evaluates how the observed state evolves relative to validated reference states, determining convergence, stabilization, transition, or divergence within conformance space.

Industrial translation therefore involves:

- Substituting laboratory surrogate surfaces with domain-specific substrates,
- Calibrating reference state libraries for each validated process stage,

- Defining tolerance envelopes consistent with metrology constraints,
- Scaling capture resolution and illumination geometry to process requirements,
- Integrating deterministic conformance evaluation into inline or at-line inspection workflows.

Importantly, no architectural shift is required between laboratory and industrial settings. The same deterministic operators apply; only the physical reference states and tolerance envelopes change.

The Ring Protocol v1 thus serves as a proof of architectural validity. Industrial deployment extends the framework into process-governed environments where deterministic state verification, stabilization monitoring, and multi-stage conformance selection are required at scale.

8.1 Chemical Mechanical Planarization (CMP)

Target Problem

In CMP processes, surface deviation often manifests as gradual state drift rather than immediately classifiable defects. Examples include:

- Micro-scratch initiation and propagation,
- Residual slurry film redistribution,
- Over-polish haze and micro-texture collapse,
- Pad-induced periodic texture shifts,
- Edge roll-off and non-uniform removal.

These conditions may not initially present as discrete, high-contrast defects. Instead, they represent structured deviation from a validated wafer surface state within tightly controlled process tolerances.

The challenge is therefore not merely defect detection, but deterministic verification of surface conformance relative to a process-defined reference condition.

Translation of SCF Modules to CMP Context

Module	CMP Application
Drift Field (Magnitude Axis)	Detects slurry redistribution, removal-rate non-uniformity, and micro-surface deviation relative to a golden wafer reference.
STRT (Spatial Axis)	Localizes scratch clusters, edge roll-off regions, or pad-pattern signatures through connected topology analysis.
DIF (Structural Axis)	Validates directional propagation of polishing artifacts (e.g., linear scratch orientation, pad sweep patterns) and distinguishes them from stochastic noise.

Module	CMP Application
SLE (Spectral Axis)	Detects micro-texture smoothing, over-polish haze, and loss of high-frequency surface structure associated with surface over-processing.
SDF (Integrated Instability Axis)	Quantifies cumulative directional reinforcement across the wafer surface, enabling domain-level instability tracking.
DAI (Temporal Axis)	Monitors instability growth during a polish cycle, detecting accelerating drift before threshold violations occur.
PADR (Admissibility Constraint)	Enforces physically plausible deviation bounds consistent with calibrated process tolerances.

Industrial Benefit

Within a CMP workflow, this architecture enables:

- Deterministic comparison to a validated golden wafer state,
- Multi-stage reference evaluation across process steps,
- Inline tracking of process drift over time,
- Early instability detection prior to visible defect manifestation or yield loss,
- Elimination of dependency on defect-class training datasets.

Importantly, the State Conformance Engine in a CMP environment functions as a real-time drift and stabilization monitor rather than a probabilistic defect classifier. It evaluates whether the wafer surface resides within an admissible conformance envelope and whether it is converging toward or diverging from validated process states.

This distinction reframes CMP inspection from reactive defect detection to proactive state governance within a structured conformance manifold.

8.2 PCB and Connector Inspection

Target Problem

In PCB manufacturing and connector assembly, many reliability-critical conditions emerge gradually as structured state deviation rather than immediately visible defects. Representative examples include:

- Solder joint micro-crack initiation,
- Connector pin warpage or misalignment,
- Surface oxidation and metallurgical texture change,

- Residual flux films and localized wetting artifacts,
- Conformal coating non-uniformity.

These phenomena often begin as subtle geometric, directional, or spectral shifts before becoming visually obvious fractures or open circuits. The challenge is therefore early instability detection relative to a validated electrical-mechanical baseline state.

Translation of SCF Modules to PCB Context

Module	PCB / Connector Application
Drift Field (Magnitude Axis)	Quantifies deviation from a validated solder or connector baseline state, capturing early surface irregularity.
STRT (Spatial Axis)	Isolates connected regions such as connector pin clusters, solder fillet boundaries, or localized oxidation zones.
DIF (Structural Axis)	Detects longitudinal crack propagation, stress-aligned gradient structure, or directional deformation patterns.
SLE (Spectral Axis)	Identifies flux-induced texture collapse, surface oxidation smoothing, or coating-induced micro-contrast attenuation.
SDF (Integrated Instability Axis)	Aggregates directional reinforcement across solder joints or connector arrays to detect domain-level instability trends.
DAI (Temporal Axis)	Monitors progressive joint instability across thermal cycling, vibration testing, or process stages.
PADR (Admissibility Constraint)	Enforces physically plausible deviation thresholds relative to calibrated assembly tolerances.

Industrial Differentiator

Unlike AI-based defect classifiers that depend on labeled crack datasets and visual similarity scoring, the SCF/SCE architecture:

- Requires no pre-labeled crack or defect class library,
- Detects structured instability prior to visible fracture manifestation,
- Operates strictly reference-relative to validated electrical-mechanical states,
- Distinguishes stochastic imaging noise from directional stress propagation.

This approach aligns with physics-informed inspection rather than statistical image categorization.

In PCB and connector environments, the State Conformance Engine functions as an instability monitor within structured conformance space. It evaluates whether solder joints and connector assemblies remain within admissible tolerance envelopes and whether emerging deviations are stabilizing or accelerating.

The result is early detection of mechanically meaningful drift, enabling proactive reliability management rather than reactive defect identification.

8.3 Thin-Film and Coating Validation

Target Problem

In optical films, protective coatings, and deposition-based manufacturing processes, deviation frequently manifests as distributed material redistribution rather than discrete geometric defects. Representative conditions include:

- Thickness non-uniformity across the substrate,
- Edge banding or boundary accumulation,
- Refractive index shifts due to compositional variation,
- Wetting anomalies during film formation,
- Haze formation and micro-texture collapse.

These phenomena often present as subtle spectral redistribution or contrast attenuation without strong edge displacement or large gradient magnitude. As a result, purely edge-driven inspection approaches may underrepresent early-stage film instability.

The inspection objective is therefore deterministic verification of film state relative to a validated optical baseline, including both structural and spectral axes.

Translation of SCF Modules to Coating Context

Module	Coating / Thin-Film Application
Drift Field (Magnitude Axis)	Detects global thickness deviation, non-uniform reflectance, or intensity variation relative to a calibrated reference film.
STRT (Spatial Axis)	Maps edge banding, boundary accumulation zones, or localized wetting clusters.
DIF (Structural Axis)	Validates deposition flow direction, identifies directional transport artifacts, and distinguishes organized redistribution from stochastic variation.
SLE (Spectral Axis)	Detects high-frequency attenuation associated with micro-texture smoothing, haze formation, or refractive redistribution.
SDF (Integrated Instability Axis)	Quantifies cumulative directional instability across the coated domain.
DAI (Temporal Axis)	Tracks film stabilization, curing dynamics, or progressive redistribution

Module	Coating / Thin-Film Application
	during drying or annealing.
PADR (Admissibility Constraint)	Enforces physically plausible deviation bounds consistent with calibrated film tolerances.

Spectral Dominance in Coating Environments

In thin-film environments, SLE becomes particularly critical. Many coating deviations manifest primarily as high-frequency attenuation rather than strong geometric gradients.

For example:

- Micro-haze formation may produce limited gradient magnitude but substantial spectral collapse.
- Wet-film redistribution may reduce micro-contrast before boundary structure becomes pronounced.
- Refractive smoothing may alter scattering behavior without discrete edge displacement.

Without a spectral axis, distributed blur-like redistribution risks being misclassified as weak anomaly or benign variation. With SLE integrated into the SCF stack, micro-texture attenuation becomes a measurable, deterministic component of conformance space.

In coating validation, the State Conformance Engine therefore functions as a structured optical state verifier, evaluating both spatial organization and spectral redistribution relative to calibrated reference films. Combined with SCE trajectory modeling, the system enables deterministic monitoring of film formation, stabilization, and process drift within a bounded conformance manifold.

8.4 Cleaning and Surface Validation

Target Problem

In precision manufacturing, post-process cleaning must be verified—not assumed.
Critical validation objectives include confirmation that:

- Residual material has been removed
- Micro-texture has been restored to its baseline scattering state
- No distributed thin wet-film or haze persists
- The surface has returned to its defined reference conformance condition

Traditional visual inspection relies on subjective assessment and may miss low-contrast distributed residue, particularly in thin-film or boundary-layer regimes. A deterministic validation method is required.

State Conformance Framework Application

Under the State Conformance architecture

state_conformance_framework

, cleaning validation is framed as a reference-relative conformance measurement problem, not an anomaly detection task.

1. Reference Establishment

A clean, operator-validated baseline is captured under controlled illumination and geometry.
This baseline represents the intended physical scattering state.

2. Spatial Localization (STRT)

Spatial Reference Tiling (STRT) partitions the surface into structured regions and evaluates deviation magnitude per tile.
This ensures that any residual cluster, boundary band, or distributed haze is geographically localized and bounded.

STRT answers:

> Where does the post-clean surface deviate from the clean baseline?

---

3. Structural Characterization (DIF)

Directional Instability Field (DIF) modeling

specification_npp15

determines whether detected deviations exhibit coherent directional structure.

Residual films or incomplete removal often produce:

- Distributed drift vectors
- Tangential boundary coherence
- Low-magnitude but spatially organized instability

DIF distinguishes:

- Physically meaningful residue

- Edge-only lighting artifacts
- Stochastic noise

DIF answers:

> Is the deviation structurally coherent and physically admissible?

---

4. Distributed vs. Boundary Residue Separation

Cleaning scenarios frequently produce three analyzable regions:

1. Exterior conformant background
2. Transitional boundary band
3. Interior distributed haze region

Interior–exterior drift contrast (Δ_{in-out}) becomes a primary metric for thin-film validation:

$$\Delta_{in-out} = \mu(drift_{inside}) - \mu(drift_{outside})$$

A positive, persistence-validated Δ_{in-out} indicates incomplete restoration of micro-texture.

---

5. Persistence Validation (PADR + PWDF)

Physics-Anchored Drift Reduction (PADR) suppresses transient artifacts.

Persistence-Weighted Drift Flux (PWDF) modeling

specification_npp15

integrates:

- Drift magnitude
- Directional coherence
- Temporal persistence

Residual films typically show:

- Distributed low-amplitude drift
- Moderate coherence density
- Temporal persistence across frames

Transient cleaning artifacts fail persistence thresholds and are suppressed.

Deterministic Conformance Confirmation

A surface is considered returned to conformance when:

- STRT spatial deviation falls below tolerance
- DIF coherence density remains below instability thresholds
- PWDF accumulation remains sub-critical
- No persistence-weighted flux accumulates beyond admissible limits

This produces a structured conformance profile rather than a binary pass/fail.

Architectural Implication

This design converts cleaning validation from:

> "Does anything look unusual?"

to

> "Has the surface returned to its defined scattering state within calibrated tolerances?"

Null results become meaningful.
Absence of structured drift confirms restoration.

Industrial Alignment

This approach aligns directly with:

- Metrology verification workflows
- Process validation protocols
- Specification-based QA procedures
- Tolerance-band conformance assessment

It avoids probabilistic defect scoring and instead produces:

- Spatial deviation maps
- Directional coherence metrics
- Persistence-weighted flux values
- Traceable, physics-grounded evidence

Conceptual Impact

Within the State Conformance Framework:

Cleaning validation is not defect detection.
It is structured verification of return-to-baseline physical state.

STRT localizes deviation.
DIF characterizes structural organization.
PWDF confirms or rejects persistence.

Together, they form a deterministic conformance loop suitable for:

- Thin-film residue validation
- Haze detection
- Post-CMP cleaning verification
- PCB wash confirmation
- Optical surface restoration checks

8.5 Process Monitoring vs. Static Inspection

The State Conformance architecture supports two complementary operational modes: **Static Conformance Mode** and **Dynamic Process Mode**. These modes operate on the same physics-anchored drift foundation but differ in temporal scope and diagnostic objective.

8.5.1 Static Conformance Mode

(Snapshot-Based Verification)

Static Conformance Mode evaluates a single captured frame relative to a validated golden reference state.

Operational Characteristics

- Compare observed frame to fixed baseline
- Execute STRT spatial localization
- Compute DIF vector field and coherence density
- Evaluate SCF conformance vector
- Apply persistence validation (short-window PADR)

- Output deterministic conformance status

Outputs

- Spatial deviation map
- Directional coherence metrics
- Persistence-weighted flux (frame-level)
- Conformance score or tolerance-band classification

In this mode, the system answers:

> Does the current surface conform to the defined expected physical state?

This is suitable for:

- Post-clean validation
- End-of-line inspection
- Wafer or PCB final QA
- Surface restoration verification

The result is not a probabilistic anomaly score, but a structured conformance profile derived from measurable physical deviation.

8.5.2 Dynamic Process Mode

(Temporal Drift Modeling and Stability Tracking)

Dynamic Process Mode extends the same drift-structured measurements across time to evaluate process evolution.

Rather than asking whether a single frame conforms, it asks:

> Is the physical state trending toward instability?

Operational Characteristics

- Capture sequential frames during active process
- Compute directional drift vectors per frame (DIF)
- Integrate Persistence-Weighted Drift Flux (PWDF)
- Compute Drift Acceleration Index (DAI)
- Track coherence density growth

- Identify Field-to-Object transition thresholds

Key Temporal Metrics

- First derivative of persistence-weighted flux (DAI_1) — instability growth rate
- Second derivative (DAI_2) — instability acceleration
- Coherence density saturation trends
- Lineage continuity validation

Dynamic Mode detects:

- Gradual thin-film buildup
- CMP haze formation
- Micro-crack precursor development
- Thermal or mechanical drift accumulation
- Pre-object instability fields

Critically, this mode identifies **pre-failure states before discrete defect emergence**.

8.5.3 Unified Drift Substrate

Both operational modes share the same underlying architecture:

- PASDE drift extraction
- PADR persistence filtering
- DIF directional encoding
- PWDF integration
- SOEC temporal gating

Static Mode uses a narrow temporal window.
Dynamic Mode expands that window into longitudinal modeling.

This preserves determinism and eliminates architectural duplication.

8.5.4 Functional Role in Industrial Environments

This dual-mode capability allows the system to operate simultaneously as:

- **Quality Assurance Instrument**
  Deterministic conformance verification against specification

- **Process Stability Monitor**
  Longitudinal drift-trend detection and pre-failure forecasting

In practical deployment:

Use Case	Mode
End-of-line surface verification	Static
In-situ wafer polishing monitoring	Dynamic
PCB wash validation	Static
Continuous conveyor-based inspection	Dynamic
Cleaning verification with haze sensitivity	Static + short-window Dynamic

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8.5.5 Strategic Implication

Traditional inspection systems are typically:

- Either snapshot QA tools
- Or separate process analytics systems

The State Conformance architecture unifies both roles under a single physics-anchored drift engine.

This integration:

- Reduces system complexity
- Ensures measurement consistency across modes
- Enables traceable linkage between final inspection failure and prior instability growth

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Summary

Static Conformance Mode confirms return-to-baseline state.
Dynamic Process Mode quantifies drift evolution and acceleration.

Together, they provide:

- Deterministic validation
- Temporal instability modeling
- Early-warning capability
- Specification-aligned output

The system therefore operates not only as a detector of non-conformance, but as a structured monitor of physical state evolution across time.

8.6 Hardware Scalability

The State Conformance architecture is hardware-agnostic by design.
It operates on drift-structured representations derived from electromagnetic scattering measurements and does not depend on a specific sensor brand, optical format, or illumination topology.

8.6.1 Platform Independence

The architecture is agnostic to:

- Camera vendor or sensor manufacturer
- Illumination configuration (brightfield, darkfield, hybrid, structured-light)
- Sensor resolution and pixel pitch
- Wavelength selection (visible, near-IR, domain-specific spectral bands)
- Single-camera or multi-camera configurations

Because the system evaluates **reference-relative drift structure**, not absolute pixel intensity, it adapts to diverse optical platforms as long as measurement conditions are internally consistent.

8.6.2 Core Hardware Requirements

While vendor-independent, the system requires adherence to three stability principles:

1. **Stable Reference Capture**
   The baseline (golden state) must be captured under fixed geometry and illumination.
   Drift measurements are reference-relative; baseline instability propagates through the conformance stack.
2. **Controlled Geometry**
   Camera angle, working distance, and focal plane must remain stable between baseline and evaluation capture.
   Geometric variance introduces structured drift unrelated to material change.
3. **Repeatable Illumination**
   Illumination intensity, directionality, and spectral composition must be consistent.
   Since DIF and PWDF model directional coherence and persistence

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   , uncontrolled lighting changes can mimic structural drift.

These requirements reflect metrology-grade repeatability standards rather than AI training constraints.

8.6.3 Illumination Sensitivity

Darkfield illumination enhances sensitivity to:

- Micro-texture variation
- Thin-film redistribution
- Boundary-layer scattering
- Early-stage surface perturbations

Darkfield increases directional scattering contrast, thereby improving:

- STRT localization precision
- DIF vector coherence detection
- Early field-to-object transition sensitivity

However, darkfield is not strictly required.
The architecture functions under brightfield or mixed configurations if reference stability is maintained.

8.6.4 Dynamic Range and Spectral Loss Extraction (SLE)

Higher sensor dynamic range improves detection in subtle redistribution scenarios, particularly when measuring:

- Thin wet-film residue
- Low-contrast haze
- Micro-texture restoration after cleaning

Spectral Loss Extraction (SLE) benefits from extended bit depth because it measures attenuation or redistribution of high-frequency scattering energy.
Low dynamic range can compress subtle spectral changes and reduce sensitivity.

Therefore:

- 12–16 bit acquisition improves thin-film resolution
- HDR pipelines enhance SLE discrimination
- Noise floor reduction improves persistence validation

8.6.5 Resolution Scaling

Increased spatial resolution does not alter the mathematical framework; it increases sampling density of the drift field.

Higher resolution enables:

- Finer STRT tiling
- Higher fidelity DIF vector maps
- Earlier detection of localized pre-object instability

However, the architecture is resolution-invariant at the modeling level.
Directional instability and persistence weighting scale across pixel densities.

This makes the system deployable on:

- Entry-level industrial cameras
- High-resolution machine-vision systems
- Line-scan platforms
- Multi-node distributed VISURA units

8.6.6 Multi-Camera and Distributed Scaling

The framework supports:

- Cross-node drift aggregation
- Multi-camera consensus
- Structured-light alignment
- Distributed PASDE architectures

Because drift is encoded as a structured field rather than an object label, conformance metrics can be aggregated across nodes while preserving physical admissibility constraints

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8.6.7 Summary

Hardware scalability is achieved not by model retraining but by enforcing measurement stability and geometric control.

The architecture requires:

- Stable baseline
- Controlled optics
- Repeatable illumination

Within those constraints, it scales across:

- Sensor classes
- Resolutions
- Wavelength regimes
- Illumination geometries

Darkfield enhances sensitivity.
Higher dynamic range improves SLE fidelity.
Resolution increases localization precision.

But the underlying conformance logic remains invariant—anchored to measurable physical drift structure rather than platform-specific pixel characteristics.

8.7 Why Deterministic Translation Matters

Industrial inspection systems do not operate in abstract research environments.
They operate within regulated, audited, and specification-bound production ecosystems.

Accordingly, inspection outputs must satisfy four foundational requirements:

- **Auditability**
- **Explainability**
- **Calibration Stability**
- **Regulatory Defensibility**

The State Conformance architecture was designed to satisfy these requirements by translating optical scattering variation into **explicit, measurable drift quantities** rather than opaque classification scores.

8.7.1 Deterministic Translation of Physical Change

In this framework, surface variation is translated into:

- Spatial deviation (STRT)
- Directional coherence (DIF)
- Persistence-weighted drift flux (PWDF)
- Drift acceleration (DAI)

Each quantity is mathematically defined

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and reference-relative

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This ensures that:

- Thresholds are explicitly defined
- Tolerance bands are numerically bounded
- Instability growth is quantifiable
- Emergence boundaries are reproducible

There is no hidden training state influencing output.

8.7.2 Contrast with Black-Box ML Systems

Conventional machine-learning inspection systems typically provide:

- Probability-of-defect scores
- Confidence metrics derived from training distributions
- Latent feature activations without physical interpretability

These systems may perform well empirically but often lack:

- Direct traceability to physical measurement
- Stability across retraining cycles
- Clear mapping between threshold adjustment and physical meaning

In contrast, the State Conformance engine provides:

- Explicit drift magnitude thresholds
- Physically interpretable coherence metrics

- Temporal derivatives tied to measurable instability
- Conformance outcomes traceable to raw field structure

If a surface fails, the system can demonstrate:

- Where deviation occurred
- How structured the deviation was
- Whether it persisted
- Whether instability accelerated

This is evidence, not inference.

8.7.3 Calibration and Regulatory Alignment

Deterministic translation enables:

- Stable calibration workflows
- Documentable acceptance criteria
- Traceable adjustment of tolerance bands
- Repeatable re-verification procedures

Threshold modification corresponds to:

- Drift magnitude change
- Coherence density adjustment
- Persistence weighting alteration

These are measurable parameters, not neural-network weight adjustments.

This distinction is critical in regulated environments.

8.7.4 Domain-Specific Importance

Deterministic conformance verification is particularly important in:

- **Semiconductor Manufacturing**
  Where wafer haze, CMP drift, and micro-defect precursors must be documented with traceable metrics.

- **Aerospace Coatings**
  Where thin-film uniformity and surface stability directly impact certification and airworthiness compliance.
- **Medical Device Validation**
  Where inspection outcomes may be subject to FDA documentation and validation protocols.
- **Automotive Electronics**
  Where PCB integrity and coating conformance must be defensible under safety and warranty audits.

In these domains, a “model confidence score” is insufficient.
Inspection results must withstand documentation review, process audit, and sometimes legal scrutiny.

8.7.5 Strategic Implication

Deterministic translation strengthens:

- Engineering credibility
- Regulatory acceptance
- Process-integration stability
- Long-term deployment viability

By grounding outputs in measurable physical drift rather than statistical anomaly likelihood, the system aligns with:

- Metrology standards
- Quality-control language
- Process-specification governance

Summary

Deterministic translation matters because industrial inspection is not merely about detection accuracy.
It is about traceability, stability, and defensibility.

The State Conformance architecture transforms optical variation into:

- Spatially localized deviation
- Directionally structured instability
- Persistence-validated flux

- Quantified acceleration trends

Each component is auditable, explainable, and physically anchored.

In high-consequence industrial environments, that distinction is not optional—it is foundational.

8.8 Deployment Pathway

Industrial deployment of the State Conformance architecture proceeds through a structured, calibration-driven sequence. Unlike model-training workflows, deployment is not data-hungry; it is reference-anchored and tolerance-defined.

The pathway is intentionally deterministic.

Phase 1 — Reference Capture

Baseline Establishment

Capture a conformant "golden state" under production-equivalent conditions:

- Production lighting geometry
- Final camera placement and focus
- Fixed working distance
- Stable environmental conditions

Multiple frames should be captured to establish:

- Baseline drift floor
- Illumination stability range
- Noise characteristics
- Initial coherence density baseline

This golden reference becomes the physical anchor for all subsequent conformance evaluation

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Key objective:

> Define the expected scattering state under controlled conditions.

Phase 2 — Tolerance Calibration

Metric Boundary Definition

Establish quantitative tolerance bands for:

- Drift magnitude threshold (τ)
- Acceptable STRT activation fraction (spatial deviation band)
- DIF coherence tolerance (directional stability limit)
- SLE attenuation limit (spectral redistribution threshold)
- PWDF accumulation ceiling
- Optional DAI growth-rate threshold (for dynamic deployment)

Calibration is performed by:

- Measuring controlled known-conformant samples
- Measuring controlled minor deviations
- Evaluating metric separation margins

This step converts physical specification into measurable conformance boundaries.

Unlike ML systems, this does not involve retraining.
It involves defining deterministic limits tied to physical drift structure

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Phase 3 — Validation Run

Controlled Deviation Confirmation

Introduce known deviation samples, such as:

- Thin-film residue
- Localized micro-perturbations
- Controlled surface texture changes
- Early-stage defect samples

Confirm that:

- STRT localizes deviation spatially
- DIF exhibits appropriate directional structure
- SLE reflects spectral redistribution
- PWDF accumulates beyond baseline
- DAI trends reflect instability growth (if temporal mode enabled)

The objective is metric separation validation:

> Demonstrate measurable gap between conformant and non-conformant states.

Validation data establishes deployment defensibility and audit readiness.

Phase 4 — Inline Monitoring

Operational Integration

After calibration and validation, the system is deployed as an inline or near-line monitoring layer.

SCF(t) — the State Conformance Function over time — may be used for:

- Real-time conformance flagging
- Batch-level acceptance validation
- Continuous process-trend tracking
- Pre-failure instability escalation

Operational modes include:

- Static Conformance Mode (snapshot QA)
- Dynamic Process Mode (temporal drift modeling)

In dynamic configurations, longitudinal metrics such as:

- PWDF accumulation
- Coherence density growth
- DAI_1 and DAI_2

support early instability detection prior to discrete defect formation.

Optional Phase 5 — Process Feedback Integration

In advanced deployments, SCF metrics can be:

- Logged into MES systems
- Linked to process parameters
- Used to trigger operator alerts
- Integrated into automated control loops

This enables closed-loop stability governance.

Deployment Philosophy

Deployment does not require:

- Large training datasets
- Periodic retraining cycles
- Opaque parameter re-optimization

Instead, it requires:

- Stable reference capture
- Quantitative tolerance definition
- Controlled validation confirmation

The result is a deterministic conformance instrument whose behavior remains stable across production cycles unless hardware geometry or baseline definitions change.

Summary

The deployment pathway proceeds through:

1. Reference establishment
2. Tolerance calibration
3. Metric separation validation
4. Inline monitoring integration

This phased structure ensures:

- Auditability
- Repeatability
- Regulatory defensibility

- Engineering transparency

The architecture transitions from laboratory calibration to production governance without altering its underlying physical-drift foundation.

8.9 Limitations and Future Expansion

The State Conformance framework is designed for deterministic, physics-anchored operation. However, translation into diverse industrial environments requires structured validation and staged expansion.

This section outlines current deployment considerations and foreseeable extensions.

8.9.1 Industrial Translation Requirements

1. Multi-Surface Validation

Different surfaces exhibit distinct scattering behaviors:

- Matte vs. polished substrates
- Metal vs. polymer vs. composite materials
- Coated vs. uncoated finishes

Because the system is reference-relative, each surface class requires:

- Dedicated golden reference capture
- Drift-floor characterization
- Surface-specific tolerance calibration

The architecture does not assume cross-surface invariance.
It requires controlled baseline establishment per material class.

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2. Illumination Invariance Testing

Although hardware-agnostic, the system is not illumination-agnostic in practice.

Controlled validation must confirm:

- Stability under minor intensity variation
- Stability under acceptable angle tolerance

- Sensitivity limits under spectral shift

Illumination drift can introduce structured scattering variation.
Therefore, invariance testing must determine:

- Acceptable illumination tolerance bands
- Calibration re-capture triggers

Future implementations may include illumination monitoring layers to detect non-material drift sources.

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3. Cross-Material Calibration Protocols

Deployment across heterogeneous production lines will require:

- Surface-class calibration profiles
- Drift-magnitude normalization across reflectivity regimes
- Dynamic range compensation tuning

This is not retraining; it is deterministic calibration per domain.

Formalized cross-material calibration procedures will improve portability across:

- Semiconductor substrates
- PCB laminates
- Aerospace coatings
- Automotive optics

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4. Extended Temporal Capture for DAI Robustness

Drift Acceleration Index (DAI) relies on temporal derivatives of persistence-weighted flux

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Robust DAI modeling requires:

- Sufficient frame sampling density
- Stable inter-frame timing
- Persistence window tuning

Short or irregular capture windows may reduce acceleration fidelity.

Future deployments should formalize:

- Minimum frame count recommendations
- Temporal resolution standards
- Process-specific sampling intervals

8.9.2 Future Architectural Extensions

The current framework is extensible without abandoning deterministic principles.

A. Divergence and Curl Analysis in DIF

Directional Instability Field (DIF) modeling currently emphasizes magnitude and coherence density.

Future enhancements may include:

- Divergence analysis ($\nabla \cdot F$) to detect field expansion or contraction
- Curl analysis ($\nabla \times F$) to identify rotational instability patterns
- Topological field structure classification

These extensions would enable:

- Early identification of circular deposition patterns
- Boundary-driven instability propagation detection
- Field-to-object transition modeling with higher sensitivity

All extensions remain vector-field analytical, not probabilistic.

B. Hierarchical Tile-Based STRT Scaling

Large wafers or panels require scalable spatial partitioning.

Future STRT extensions may include:

- Adaptive recursive tiling
- Multi-resolution spatial pyramids
- Region-priority refinement (attention based on drift topology)

This enables:

- Efficient large-area monitoring
- High-resolution localization without full-frame computational burden
- Scalable wafer-scale deployment

C. Multi-Spectral SLE Expansion

Spectral Loss Extraction (SLE) may be extended beyond single-channel intensity analysis.

Future enhancements include:

- Multi-wavelength attenuation profiling
- Cross-band spectral redistribution modeling
- Thin-film thickness sensitivity tuning

Multi-spectral SLE would increase sensitivity in:

- Coating uniformity assessment
- Film chemistry variation
- Surface oxidation or contamination differentiation

D. Automated Conformance Envelope Learning

(Deterministic, Not Probabilistic)

Future systems may incorporate:

- Deterministic envelope adaptation
- Drift-floor trend modeling
- Specification-bound tolerance auto-adjustment

Importantly:

This would not involve probabilistic defect modeling.

Instead, it would:

- Learn stable tolerance envelopes
- Track baseline drift shifts
- Alert when recalibration is required

This preserves the deterministic character of the architecture.

8.9.3 Strategic Position

The framework is mature for controlled industrial deployment but requires structured validation across:

- Surface classes
- Illumination regimes
- Temporal scales

Future extensions focus on:

- Enhanced field mathematics
- Scalable tiling
- Multi-spectral depth
- Deterministic tolerance adaptation

At no point does expansion require black-box retraining.

All growth remains anchored to measurable drift structure and reference-relative conformance logic.

8.10 Summary of Section 8

The Ring Protocol v1 establishes experimental feasibility by demonstrating measurable separation between conformant and non-conformant scattering states under controlled laboratory conditions.

Industrial translation establishes practical applicability by showing how the same reference-relative drift architecture can be calibrated, validated, and deployed in production environments.

Together, these confirm both conceptual and operational viability.

The State Conformance Engine

The State Conformance Engine integrates spatial, structural, spectral, and temporal analysis layers into a unified deterministic framework:

- **Spatial Localization (STRT)**
  Partitions the surface and identifies where deviation from baseline occurs.
- **Directional Validation (DIF)**
  Quantifies vector coherence and structural organization of drift fields

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- **Temporal Evolution Tracking (DAI)**
  Measures instability growth and acceleration across time, enabling pre-failure detection.
- **Magnitude Enforcement (PADR)**
  Suppresses transient artifacts and enforces persistence-weighted admissibility.
- **Spectral Redistribution Detection (SLE)**
  Identifies attenuation and redistribution of high-frequency scattering energy in thin-film and haze scenarios.

These layers operate over a common drift substrate and are anchored to a defined reference state

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Domain Breadth

Across:

- CMP surface processing
- PCB micro-instability detection
- Thin-film residue validation
- Coating uniformity assessment

the architecture consistently transforms inspection from object-centric defect detection into structured state verification.

It detects not only discrete defects, but distributed field instability and pre-object emergence conditions.

Conceptual Shift

The transformation enabled by this architecture is not merely technical.

Traditional inspection systems ask:

> Does this look anomalous?

The State Conformance Engine asks:

> Does this measured physical state conform to the defined expected state?

This reframing changes:

- The epistemology of inspection
- The regulatory posture of outputs
- The engineering credibility of results

Conformance is not inferred from probability distributions.

It is measured against a defined baseline using physically interpretable drift metrics.

Foundational Principle

Conformance is measured, not inferred.

Deviation is spatially localized.
Structure is directionally validated.
Persistence is temporally confirmed.
Spectral redistribution is quantified.

The result is a deterministic verification instrument suitable for industrial environments requiring auditability, explainability, and defensibility.

Section 8 therefore establishes both:

- Experimental feasibility
- Industrial translation pathway
- Conceptual redefinition of inspection

and positions the State Conformance Engine as a structured, physics-anchored alternative to anomaly-based classification systems.

9. Comparative Analysis, Failure Modes, and Formal SCF Aggregation

Section 7 established the industrial translation pathway of the State Conformance Engine.
This section formalizes:

1. How SCF differs from ML-first anomaly systems
2. Known failure modes and boundary conditions

3. A mathematical aggregation model for SCF(t)

The goal is to clarify operational limits while strengthening the deterministic foundation of the framework.

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9. Comparative Analysis, Failure Modes, and Formal SCF Aggregation

Section 8 established the industrial deployment pathway of the State Conformance Engine and demonstrated feasibility across laboratory and production contexts.

This section formalizes three critical aspects of the framework:

1. How State Conformance (SCF) differs structurally and epistemologically from ML-first anomaly systems
2. Known failure modes and boundary conditions
3. A mathematical aggregation model for SCF(t), the State Conformance Function over time

The objective is not merely contrast, but clarification of operational limits while strengthening the deterministic foundation of the architecture

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9.1 Comparative Analysis: SCF vs ML-First Anomaly Systems

9.1.1 Foundational Difference

Machine-learning-first inspection systems typically operate by:

- Learning a statistical distribution of “normal” samples
- Encoding features in latent space
- Assigning anomaly probability or confidence scores

The epistemology is probabilistic and distribution-relative.

By contrast, the State Conformance Framework operates by:

- Establishing a defined physical reference state

- Measuring spatially localized deviation
- Quantifying directional coherence
- Validating persistence and admissibility
- Tracking temporal acceleration

The epistemology is deterministic and reference-relative

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9.1.2 Structural Comparison

Dimension	ML-First Systems	State Conformance Framework
Baseline	Learned distribution	Defined golden state
Output	Probability / score	Drift metrics
Explainability	Feature importance (often opaque)	Spatial + directional maps
Calibration	Retraining required	Threshold adjustment
Drift Tracking	Model drift (data shift)	Physical drift (field evolution)
Regulatory Defense	Performance-based	Measurement-based

SCF outputs are physically interpretable quantities:

- STRT spatial deviation fraction
- DIF coherence density
- PWDF accumulation
- DAI growth and acceleration

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This makes conformance measurable rather than inferred.

9.1.3 Practical Implication

ML systems are optimized for classification accuracy across diverse unknown patterns.

SCF is optimized for:

- Specification enforcement
- Stability monitoring
- Pre-failure instability detection

- Audit-ready documentation

The difference is not superiority in all cases.
It is difference in mission and structure.

9.2 Known Failure Modes and Boundary Conditions

A deterministic framework must clearly state its operational limits.

9.2.1 Illumination Drift

If illumination geometry changes significantly between baseline and evaluation:

- Structured scattering shifts may occur
- False drift vectors may emerge
- DIF coherence may artificially increase

Mitigation:

- Illumination monitoring
- Reference re-capture triggers
- Geometry locking

9.2.2 Geometric Misalignment

Camera repositioning or focus shift introduces systematic drift unrelated to material change.

Mitigation:

- Fixed mounts
- Mechanical indexing
- Baseline stability validation

9.2.3 Global Environmental Shifts

Temperature-driven expansion or vibration may create distributed low-amplitude drift.

Mitigation:

- Persistence weighting (PADR)

- Environmental tolerance bands
- Cross-frame stability thresholds

9.2.4 Ultra-Low Contrast Regimes

If signal amplitude approaches sensor noise floor:

- SLE discrimination decreases
- DIF vector stability may degrade
- DAI may become unstable

Mitigation:

- Higher dynamic range sensors
- Darkfield enhancement
- Frame averaging

9.2.5 Legitimate Process State Transitions

Some industrial processes intentionally alter surface state (e.g., coating stages).

In these cases:

- Baseline must be stage-specific
- SCF thresholds must be context-dependent

The system does not decide intent.
It measures deviation from the defined reference.

9.3 Formal Aggregation Model for SCF(t)

The State Conformance Function aggregates spatial, structural, spectral, and temporal components into a bounded scalar or vector representation.

Let:

- S(t) = STRT spatial deviation fraction
- K(t) = DIF coherence density
- F(t) = Persistence-Weighted Drift Flux (PWDF)

- $A_1(t) = DAI_1$ (first derivative of F)
- $A_2(t) = DAI_2$ (second derivative of F)
- L(t) = Spectral Loss metric (SLE aggregate)

A generalized aggregation form:

SCF(t)=wsS(t)+wkK(t)+wfF(t)+wa1A1(t)+wa2A2(t)+wlL(t)SCF(t) = w_s S(t) + w_k K(t) + w_f F(t) + w_{a1} A_1(t) + w_{a2} A_2(t) + w_l L(t)SCF(t)=wsS(t)+wkK(t)+wfF(t)+wa1A1(t)+wa2A2(t)+wl L(t)

where:

- w_i are deterministic weighting coefficients
- All inputs are physically measurable quantities

For static inspection:

SCFstatic=wsS+wkK+wfF+wlLSCF_{static} = w_s S + w_k K + w_f F + w_l LSCFstatic=wsS+wk K+wfF+wlL

For dynamic monitoring:

SCFdynamic(t)=SCFstatic(t)+wa1A1(t)+wa2A2(t)SCF_{dynamic}(t) = SCF_{static}(t) + w_{a1} A_1(t) + w_{a2} A_2(t)SCFdynamic(t)=SCFstatic(t)+wa1A1(t)+wa2A2(t)

Thresholding operates on:

- Component-wise limits
- Or aggregated SCF(t) envelope

Importantly:

SCF(t) is not a learned classifier output.
It is a deterministic aggregation of measurable field properties.

9.3.1 Vector Formulation (Optional Extension)

In advanced implementations, SCF may remain vector-valued:

SCF(t)=[S(t),K(t),F(t),A1(t),A2(t),L(t)]\mathbf{SCF}(t) = \big[S(t), K(t), F(t), A_1(t), A_2(t), L(t)\big]SCF(t)=[S(t),K(t),F(t),A1(t),A2(t),L(t)]

Decision logic then evaluates:

- Component thresholds
- Persistence duration

- Acceleration trends

This preserves interpretability and avoids collapsing information prematurely.

9.4 Operational Limits and Strength

The strength of SCF lies in:

- Reference anchoring
- Explicit thresholds
- Physical interpretability
- Persistence validation

Its limits lie in:

- Dependence on baseline stability
- Sensitivity to uncontrolled geometry change
- Need for domain-specific calibration

These are engineering constraints, not epistemological weaknesses.

9.5 Closing Position

Section 9 clarifies that the State Conformance Framework is not a general-purpose anomaly classifier.

It is a deterministic measurement architecture that:

- Quantifies spatial deviation
- Validates directional structure
- Integrates persistence-weighted flux
- Tracks acceleration of instability

SCF(t) formalizes these quantities into a unified conformance function.

By explicitly defining:

- Differences from ML systems
- Failure modes
- Mathematical aggregation

the framework strengthens its defensibility, auditability, and industrial credibility.

Conformance is computed from measurable drift structure.

It is not inferred from probability.

10.0 Conclusion and Forward Position

Sections 1–9 established the conceptual foundation, mathematical formalism, experimental feasibility, industrial translation pathway, comparative positioning, and deterministic aggregation model of the State Conformance Framework (SCF).

This final section consolidates the technical thesis and defines the forward trajectory of the architecture.

10.1 Core Thesis

The central proposition of this work is that inspection should be reframed from probabilistic anomaly inference to deterministic state verification.

Under the State Conformance Framework

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:

- A defined physical baseline is intentionally captured.
- Deviation from that baseline is spatially localized.
- Structural organization of deviation is directionally quantified.
- Temporal persistence and acceleration are measured.
- Spectral redistribution is explicitly evaluated.

The system does not infer abnormality from statistical rarity.

It measures divergence from a known expected state.

This shift is foundational.

10.2 Integrated Architecture

The State Conformance Engine integrates:

- **STRT —** Spatial localization of deviation
- **DIF —** Directional instability field modeling

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- **PADR —** Persistence and admissibility enforcement
- **PWDF —** Accumulated drift flux quantification
- **DAI —** Instability growth and acceleration tracking
- **SLE —** Spectral redistribution detection

Together, these components operate over a unified drift substrate.

The architecture supports:

- Snapshot conformance validation
- Longitudinal process monitoring
- Pre-object instability detection
- Deterministic threshold enforcement

Each component is mathematically defined and physically interpretable.

10.3 Practical Impact

Across CMP, PCB, thin-film, and coating domains, the framework enables:

- Early-stage distributed instability detection
- Thin-film haze validation
- Micro-perturbation monitoring prior to fracture
- Return-to-baseline confirmation after cleaning

This allows inspection to move upstream in the failure timeline.

Rather than detecting finished defects, the system detects field-level instability accumulation.

10.4 Deterministic Governance

Industrial inspection requires:

- Auditability
- Calibration stability
- Regulatory defensibility
- Transparent threshold control

The State Conformance architecture satisfies these requirements by:

- Using explicit reference capture
- Employing measurable drift metrics
- Defining bounded tolerance envelopes
- Avoiding opaque retraining cycles

If thresholds are adjusted, the adjustment is physically interpretable.

If failure is declared, the failure is measurable and reproducible.

10.5 Conceptual Advancement

The broader contribution of this work is conceptual as well as technical.

Conventional inspection systems are object-centric and classification-driven.

The State Conformance Framework is field-centric and verification-driven.

It models:

- Distributed energy redistribution
- Directional coherence growth
- Persistence-weighted accumulation
- Acceleration toward emergence

In this framing, defects are not primary entities.

They are outcomes of prior field instability.

This permits earlier detection and deeper interpretability.

10.6 Limitations and Responsible Scope

The framework does not claim:

- Universal illumination invariance
- Automatic cross-material generalization
- Independence from baseline quality

It requires:

- Controlled reference capture
- Domain-specific calibration
- Stability in optical geometry

These constraints are engineering requirements consistent with metrology practice.

10.7 Forward Trajectory

Future work may extend:

- Higher-order field topology (divergence/curl)
- Multi-spectral SLE modeling
- Adaptive but deterministic tolerance envelopes
- Large-area hierarchical tiling
- Closed-loop process feedback integration

All expansions preserve the core principle:

Conformance must remain measurable, interpretable, and reference-anchored.

10.8 Final Position

The State Conformance Framework establishes a deterministic inspection paradigm grounded in measurable drift structure.

It transforms inspection from:

“Is this statistically unusual?”

to:

“Does this measured physical state conform to the defined expected condition?”

This is not a refinement of anomaly detection.

It is a reframing of inspection philosophy.

Conformance is computed.
Deviation is localized.
Structure is validated.
Persistence is confirmed.
Acceleration is quantified.

Conformance is measured — not inferred.

Appendix A — Formal Mathematical Definitions

Appendix A provides explicit mathematical formalization of the core operators underlying the State Conformance Framework (SCF). The purpose is to remove ambiguity, define admissibility conditions, and clarify deterministic behavior.

A.1 Formal Expansion of the VAAD Operator

The drift field is defined as:

D(x,y,t)=VAAD(I(x,y,t))D(x,y,t) = \text{VAAD}(I(x,y,t))D(x,y,t)=VAAD(I(x,y,t))

We expand VAAD as a deterministic composite operator:

VAAD=Πp∘N∘G∘Δ\text{VAAD} = \Pi_p \circ \mathcal{N} \circ \mathcal{G} \circ \DeltaVAAD=Πp∘N∘G∘Δ

Where:

- Δ\DeltaΔ = reference-relative subtraction
- G\mathcal{G}G = multi-scale gradient filtering
- N\mathcal{N}N = local normalization

- Π_p = persistence weighting operator

A.1.1 Reference Subtraction

Let baseline reference be:

$$I_0(x,y)$$

Deviation is:

$$\Delta I(x,y,t) = I(x,y,t) - I_0(x,y)$$

Assumption: I_0 is captured under stable illumination and geometry.

A.1.2 Multi-Scale Gradient Operator

Define a scale set $\Sigma = \{\sigma_1, \sigma_2, ..., \sigma_k\}$.

At each scale:

$$G_\sigma(x,y,t) = \nabla \big(\mathcal{S}_\sigma * \Delta I(x,y,t) \big)$$

Where:

- $\mathcal{S}_\sigma$ = Gaussian smoothing kernel
- $*$ = convolution
- ∇ = gradient operator

Multi-scale aggregation:

$$G(x,y,t) = \sum_{\sigma \in \Sigma} w_\sigma |G_\sigma(x,y,t)|$$

This enhances structural sensitivity across spatial frequencies.

A.1.3 Local Normalization

To reduce illumination bias:

$$\mathcal{N}(x,y,t) = \frac{G(x,y,t)}{\sigma_{local}(x,y) + \epsilon}$$

Where:

- $\sigma_{local}(x,y)$ = local standard deviation window
- ϵ = small stabilizing constant

This enforces scale invariance under moderate brightness shifts.

A.1.4 Persistence Weighting (PADR)

Define persistence over window T_p:

$$\Pi_p(x,y,t) = \frac{1}{T_p} \sum_{k=0}^{T_p-1} \mathcal{N}(x,y,t-k)$$

Only regions satisfying:

$$\Pi_p(x,y,t) > \tau_p$$

are considered admissible drift.

Final drift field:

$$D(x,y,t) = \Pi_p(x,y,t)$$

A.2 STRT Topology Formalization

Given drift field $D(x,y)$:

Binary activation:

$$M(x,y) = \mathbb{1}(D(x,y) > \tau)$$

Where:

- τ = deterministic drift threshold

A.2.1 Connectivity Definition

Let adjacency be defined as:

- 4-connectivity:

  $$(x,y) \leftrightarrow (x\pm1,y), (x,y\pm1)$$
- or 8-connectivity (optional extension)

Connected components:

{CCi}\{ CC_i \}{CCi}

A.2.2 Largest Connected Component Ratio

Lcc=maxiarea(CCi)∑iarea(CCi)L_{cc} = \frac{\max_i \text{area}(CC_i)} {\sum_i \text{area}(CC_i)}Lcc=∑iarea(CCi)maxiarea(CCi)

Bounds:

0≤Lcc≤10 \le L_{cc} \le 10≤Lcc≤1

Properties:

- Lcc=1L_{cc} = 1Lcc=1 if single connected cluster
- Lcc→0L_{cc} \to 0Lcc→0 if fragmentation dominates

A.2.3 Activation Fraction

S=1N∑x,yM(x,y)S = \frac{1}{N} \sum_{x,y} M(x,y)S=N1x,y∑M(x,y)

Where NNN = total pixels.

A.3 DIF Circular Coherence Formalization

Gradient:

∇D(x,y)=[∂D∂x,∂D∂y]\nabla D(x,y) = \left[\frac{\partial D}{\partial x}, \frac{\partial D}{\partial y} \right]∇D(x,y)=[∂x∂D,∂y∂D]

Orientation:

θ(x,y)=arctan2(∂D∂y,∂D∂x)\theta(x,y) = \arctan2 \left(\frac{\partial D}{\partial y}, \frac{\partial D}{\partial x} \right)θ(x,y)=arctan2(∂y∂D,∂x∂D)

Weight:

wi=∣∇Di∣w_i = |\nabla D_i|wi=∣∇Di∣

Directional coherence:

K=∣∑iwiejθi∣∑iwiK = \frac{\left| \sum_i w_i e^{j\theta_i} \right|} {\sum_i w_i}K=∑iwi∑iwiejθi

Properties:

0≤K≤10 \le K \le 10≤K≤1

- $K=1$: perfect alignment
- $K=0$: isotropic orientation

This is equivalent to the mean resultant length in circular statistics.

A.4 DAI Stability Formalization

Let $P(t)$ be any structured metric.

Discrete derivatives:

$$DAI_1(t_k) = \frac{P(t_k) - P(t_{k-1})}{\Delta t}$$

$$DAI_2(t_k) = \frac{P(t_k) - 2P(t_{k-1}) + P(t_{k-2})}{(\Delta t)^2}$$

Stability condition:

$$|DAI_1| < \alpha \quad \text{and} \quad |DAI_2| < \beta$$

define bounded-state region.

Persistent positive:

$$DAI_2 > 0$$

implies divergence from equilibrium.

A.5 SLE Spectral Formalization

Let high-frequency operator $\mathcal{H}$:

$$HF(x,y) = |\mathcal{H}(I(x,y))|$$

Possible implementations:

1. Laplacian:

$$\mathcal{H} = \nabla^2$$

2. High-pass filter:

$$\mathcal{H} = I - (G_\sigma * I)$$

3. FFT band-pass.

Spectral loss:

SLE(x,y)=max(0,HFgolden(x,y)−HFcurrent(x,y))SLE(x,y) = \max(0, HF_{golden}(x,y) - HF_{current}(x,y))SLE(x,y)=max(0,HFgolden(x,y)−HFcurrent(x,y))

Global metric:

SLEmean=1N∑x,ySLE(x,y)SLE_{mean} = \frac{1}{N} \sum_{x,y} SLE(x,y)SLEmean=N1x,y∑ SLE(x,y)

A.6 Admissibility Conditions for Physical Legitimacy

A deviation region R⊂ΩR \subset \OmegaR⊂Ω is considered physically admissible if:

1. Persistence condition:

Πp(x,y,t)>τp\Pi_p(x,y,t) > \tau_pΠp(x,y,t)>τp

2. Topological consistency:

area(CCi)>Amin\text{area}(CC_i) > A_{min}area(CCi)>Amin

3. Structural reinforcement:

KR>KminorSLER>SLEminK_R > K_{min} \quad \text{or} \quad SLE_R > SLE_{min}KR>Kmin orSLER>SLEmin

This multi-axis condition suppresses stochastic artifacts.

A.7 Deterministic Conformance Envelope

Define:

v(t)=[S(t),K(t),P(t),SLE(t),DAI1(t),DAI2(t)]\mathbf{v}(t) = [S(t), K(t), P(t), SLE(t), DAI_1(t), DAI_2(t)]v(t)=[S(t),K(t),P(t),SLE(t),DAI1(t),DAI2(t)]

Conformance region:

E={v∣S≤Smax,K≤Kmax,P≤Pmax,SLE≤SLEmax,∣DAI1∣≤A1,∣DAI2∣≤A2}\mathcal{E} = \{ \mathbf{v} \mid S \le S_{max}, K \le K_{max}, P \le P_{max}, SLE \le SLE_{max}, |DAI_1| \le A_1, |DAI_2| \le A_2 \}E={v∣S≤Smax,K≤Kmax,P≤Pmax,SLE≤SLEmax,∣DAI1∣≤A1,∣DAI2∣≤A2}

Deviation outside E\mathcal{E}E implies loss of conformance.

A.8 Determinism Statement

All operators defined above are:

- Algebraic
- Convolutional
- Threshold-based
- Derivative-based

None require:

- Learned parameters
- Training datasets
- Distribution fitting
- Probabilistic inference

Thus SCF is formally deterministic.

Appendix A — Terminology, Symbols, and Formal Definitions

This appendix consolidates the terminology, symbols, and mathematical constructs used throughout the State Conformance Framework (SCF). It reflects the expanded architecture including STRT, DIF, PADR, PWDF, DAI, SLE, and SCF(t) aggregation.

The purpose of this appendix is to ensure mathematical clarity, auditability, and regulatory defensibility.

A.1 Core Conceptual Definitions

State Conformance Framework (SCF)

A deterministic, reference-relative measurement architecture that evaluates whether an observed physical state conforms to a defined baseline by quantifying structured drift.

SCF operates on:

- Spatial deviation

- Directional organization
- Temporal persistence
- Spectral redistribution

Conformance is computed, not inferred.

Golden Reference (Baseline State)

A validated conformant physical state captured under controlled geometry and illumination.

All drift measurements are defined relative to this baseline.

Drift Field $D(x,y,t)$

A spatially resolved representation of measurable deviation between the observed state and the reference state at time t.

$$D(x,y,t) = f(\text{observed}(x,y,t), \text{reference}(x,y))$$

Drift may represent:

- Intensity redistribution
- Gradient shift
- Spectral attenuation
- Structured scattering change

A.2 Spatial Metrics

STRT — Spatial Reference Tiling

Partitions the surface into structured tiles and evaluates spatial deviation.

Let:

$$S(t) = \frac{\text{Number of tiles exceeding drift threshold } \tau}{\text{Total tiles}}$$

Where:

- $S(t)$ = Spatial deviation fraction

- τ = Drift magnitude threshold

L_{cc} — Largest Connected Component Ratio

Measures the spatial connectivity of activated tiles:

$$L_{cc} = \frac{\text{Area of largest connected deviation region}}{\text{Total active deviation area}}$$

Used to distinguish distributed haze from localized defect clusters.

A.3 Directional Metrics

DIF — Directional Instability Field

A vector field representation of drift orientation and magnitude.

$$\mathbf{F}(x,y,t) = \left[F_x(x,y,t), F_y(x,y,t) \right]$$

Derived from spatial gradients or directional drift decomposition.

$K(t)$ — Coherence Density

Quantifies directional alignment within active drift regions.

$$K(t) = \frac{\left\| \sum \mathbf{F}(x,y,t) \right\|}{\sum \|\mathbf{F}(x,y,t)\|}$$

Where:

- $K(t) \in [0,1]$
- High values indicate structured directional coherence
- Low values indicate stochastic distribution

Optional Future Extensions

- Divergence: $\nabla \cdot \mathbf{F}$
- Curl: $\nabla \times \mathbf{F}$

Used for topological classification of instability fields.

A.4 Spectral Metrics

SLE — Spectral Loss Extraction

Measures redistribution or attenuation of high-frequency scattering energy.

$$L(t) = \max(0, HF_{ref}(x,y) - HF_{obs}(x,y,t))$$

Where:

- HF denotes high-frequency spectral component
- Positive values indicate spectral attenuation

SLE is especially sensitive to thin-film residue and haze redistribution.

A.5 Persistence and Flux Metrics

PADR — Persistence-Admissible Drift Reduction

A temporal filtering mechanism that suppresses transient, non-persistent drift.

Only drift exceeding persistence criteria contributes to flux accumulation.

PWDF — Persistence-Weighted Drift Flux

Cumulative measure of admissible drift over time.

$$F(t) = \int_{t_0}^{t} w_p(\tau) \cdot \|D(\tau)\| d\tau$$

Where:

- $w_p(\tau)$ is persistence weighting
- $F(t)$ accumulates structured instability energy

A.6 Temporal Metrics

DAI$_1$ — Drift Acceleration Index (First Derivative)

A1(t)=dF(t)dtA_1(t) = \frac{dF(t)}{dt}A1(t)=dtdF(t)

Represents instability growth rate.

DAI$_2$ — Drift Acceleration Index (Second Derivative)

A2(t)=d2F(t)dt2A_2(t) = \frac{d^2F(t)}{dt^2}A2(t)=dt2d2F(t)

Represents acceleration of instability accumulation.

Persistent positive A2(t)A_2(t)A2(t) may indicate pre-transition instability buildup.

A.7 SCF Aggregation Model

The State Conformance Function may be defined as either scalar or vector form.

Scalar Form

SCF(t)=wsS(t)+wkK(t)+wfF(t)+wa1A1(t)+wa2A2(t)+wlL(t)SCF(t) = w_s S(t) + w_k K(t) + w_f F(t) + w_{a1} A_1(t) + w_{a2} A_2(t) + w_l L(t)SCF(t)=wsS(t)+wkK(t)+wfF(t)+wa1A1(t)+wa2A2(t)+wl L(t)

Where:

- wiw_iwi are deterministic weighting coefficients
- All components are physically measurable

Vector Form (Preferred for Auditability)

SCF(t)=[S(t),K(t),F(t),A1(t),A2(t),L(t)]\mathbf{SCF}(t) = \big[S(t), K(t), F(t), A_1(t), A_2(t), L(t) \big]SCF(t)=[S(t),K(t),F(t),A1(t),A2(t),L(t)]

Decision logic may evaluate:

- Component-wise thresholds
- Persistence duration

- Acceleration boundaries

Vector form preserves interpretability.

A.8 Threshold and Tolerance Definitions

Drift Threshold τ\tauτ

Minimum magnitude required for spatial activation.

Coherence Threshold κ\kappaκ

Minimum directional alignment required for structural classification.

Spectral Attenuation Limit λ\lambdaλ

Maximum allowable SLE aggregate value for conformance.

Acceleration Limit α\alphaα

Upper bound on DAI_2 prior to instability escalation flag.

A.9 Boundary Conditions

SCF validity assumes:

- Stable baseline capture
- Controlled illumination geometry
- Consistent focal plane
- Sufficient signal-to-noise ratio

Violations of these conditions may introduce structured non-material drift.

A.10 Conceptual Summary of Appendix A

This appendix formalizes the State Conformance Framework as a deterministic, reference-relative measurement system built upon:

- Spatial deviation quantification
- Directional vector field analysis
- Spectral redistribution measurement
- Persistence-weighted flux accumulation
- Temporal acceleration modeling

Every symbol corresponds to a measurable physical quantity.

No component represents probabilistic inference.

The framework remains:

- Auditable
- Calibratable
- Interpretable
- Defensible

Conformance is defined mathematically.
Deviation is bounded explicitly.
Instability is tracked deterministically.

Appendix B — State Conformance Theorem (Formal Statement and Proof Sketch)

This appendix formalizes the deterministic foundation of the State Conformance Framework (SCF). It defines admissibility conditions under which a measured deviation constitutes a physically meaningful non-conformant state.

The purpose of this appendix is to strengthen the mathematical defensibility of the framework and clarify its boundary conditions.

B.1 Formal Definitions

Let:

- $R(x,y)$ denote a validated reference (golden) state.
- $O(x,y,t)$ denote an observed state at time t.
- $D(x,y,t)$ denote the drift field defined as a measurable deviation between O and R.

$$D(x,y,t) = f(O(x,y,t), R(x,y))$$

Let:

- $S(t)$ = spatial activation fraction (STRT)
- $K(t)$ = directional coherence density (DIF)
- $F(t)$ = persistence-weighted drift flux (PWDF)
- $A_1(t) = \frac{dF}{dt}$ = first temporal derivative (DAI_1)
- $A_2(t) = \frac{d^2F}{dt^2}$ = second temporal derivative (DAI_2)
- $L(t)$ = spectral loss aggregate (SLE)

B.2 State Conformance Theorem (Primary Form)

Theorem (Deterministic Conformance Admissibility)

If measurable deviation produces:

1. Non-zero spatial activation above threshold τ,
2. Directional coherence exceeding structural tolerance κ,
3. Persistence-weighted flux accumulation beyond admissible limit,
4. Or sustained positive temporal acceleration $A_2(t) > 0$ under stable boundary conditions,

then the observed state $O(x,y,t)$ is non-conformant relative to reference state $R(x,y)$.

Conversely, if all bounded thresholds remain satisfied under stable measurement conditions, the observed state is conformant.

B.3 Proof Sketch (Conceptual)

The proof is constructive and based on deterministic measurement properties.

Step 1 — Reference-Relative Measurement

Drift is defined relative to a fixed reference.
Under stable geometry and illumination:

D(x,y,t)=0iffO(x,y,t)=R(x,y)D(x,y,t) = 0 \quad \text{iff} \quad O(x,y,t) = R(x,y)D(x,y,t)=0iffO(x,y,t)=R(x,y)

Thus, zero drift implies identical scattering state.

Step 2 — Spatial Thresholding

If drift magnitude exceeds threshold τ\tauτ across a spatial fraction S(t)S(t)S(t), then measurable deviation exists beyond noise floor.

Spatial deviation is therefore bounded and observable.

Step 3 — Structural Coherence

Random noise produces low coherence density:

K(t)≈0K(t) \approx 0K(t)≈0

Structured physical change produces:

K(t)>κK(t) > \kappaK(t)>κ

Thus, coherence distinguishes stochastic fluctuation from organized material variation.

Step 4 — Persistence Weighting

Transient disturbances fail persistence gating.

If flux accumulates:

F(t)>ϕF(t) > \phiF(t)>ϕ

where ϕ\phiϕ is admissible flux limit, then deviation is temporally sustained.

Persistence eliminates single-frame artifacts.

Step 5 — Acceleration Condition

If:

$$A_2(t) = \frac{d^2F}{dt^2} > 0$$

for sustained intervals, instability is accelerating.

Acceleration indicates pre-transition instability buildup.

Conclusion

Because each condition is:

- Measurable,
- Threshold-bound,
- Reference-relative,

the classification of conformant vs non-conformant state is deterministic under stable boundary conditions.

B.4 Boundary Conditions

The theorem assumes:

- Stable illumination geometry
- Fixed optical alignment
- Adequate signal-to-noise ratio
- Accurate reference capture

Violation of these assumptions may introduce non-material drift.

The theorem therefore applies under controlled metrological conditions.

B.5 Corollary 1 — Field-to-Object Transition

If:

- Spatial activation increases,
- Coherence density increases,
- Persistence-weighted flux accumulates,
- Acceleration remains positive,

then distributed field instability may transition into discrete defect manifestation.

This formalizes pre-object detection capability.

B.6 Corollary 2 — Spectral Redistribution Admissibility

If spectral loss $L(t)$L(t)$L(t)$ exceeds threshold while spatial coherence remains bounded, the system may classify thin-film redistribution or haze formation without discrete clustering.

This supports non-defect distributed state deviation classification.

B.7 Corollary 3 — Null Stability

If:

$S(t)<\tau_s, K(t)<\kappa, F(t)<\phi, |A_1(t)|\approx 0, A_2(t)\le 0$S(t) < \tau_s, \quad K(t) < \kappa, \quad F(t) < \phi, \quad |A_1(t)| \approx 0, \quad A_2(t) \le 0$S(t)<\tau_s, K(t)<\kappa, F(t)<\phi, |A_1(t)|\approx 0, A_2(t)\le 0$

then the state is stable and conformant.

Absence of structured drift is itself a measurable confirmation.

B.8 Deterministic vs Probabilistic Distinction

This theorem does not rely on:

- Learned distributions
- Training data variance

- Probability-of-defect metrics

Instead, it relies on:

- Explicit thresholds
- Field structure quantification
- Temporal derivatives

The admissibility decision is computed, not inferred.

B.9 Interpretation and Scope

The State Conformance Theorem formalizes the following principle:

A physical state is non-conformant if and only if measurable, structured, persistent deviation from the defined baseline exceeds bounded thresholds under stable measurement conditions.

This ensures:

- Auditability
- Explainability
- Regulatory defensibility
- Calibration transparency

B.10 Summary of Appendix B

Appendix B provides:

- Formal admissibility criteria
- Constructive proof logic
- Boundary condition clarification
- Corollary structure for distributed and accelerating instability

The theorem strengthens the deterministic claim of the framework by demonstrating that conformance decisions are mathematically anchored to measurable drift structure.

Conformance is defined by bounded field behavior.

Non-conformance emerges from structured, persistent, accelerating deviation.

The framework therefore operates within a rigorously defined deterministic measurement space.

Appendix C — Region-Structured State Conformance and Adaptive Analytical Focus

C.1 Purpose of This Appendix

This appendix formalizes the region-based interpretation layer within the State Conformance Framework (SCF). It extends the STRT → DIF → LDE stack by defining how spatial regions are identified, evaluated, and selectively refined when structured deviation emerges.

The goal is not to "detect anomalies," but to:

1. Identify where deviation from a defined reference state occurs.
2. Characterize the structural and directional properties of that deviation.
3. Allocate computational refinement where diagnostic value is highest.
4. Confirm conformance or quantify structured divergence.

C.2 From Pixel Deviation to Topological Regions

Drift maps derived from PADR and STRT partition the surface into spatial tiles. However, physical deviation rarely manifests as isolated pixels. Instead, it organizes into topological regions.

A generalized perturbation (e.g., thin-film haze, coffee-ring deposition, micro-crack precursor) typically contains at least three analytically distinct regions:

(1) Exterior Reference Region

Nominal surface texture, intended to conform to baseline state.

(2) Transition / Boundary Region

High-gradient interface between states; often spatially coherent and directionally structured.

(3) Interior Perturbation Region

Distributed, low-contrast drift consistent with thin-film redistribution, haze, or field-level instability.

This three-region topology is not specific to coffee-ring experiments. It generalizes to:

- PCB micro-fracture precursors
- Wafer CMP haze formation
- Thin-film redistribution
- Localized contamination boundaries
- Structured-light perturbations

C.3 STRT as Region Proposal Mechanism

STRT (Spatial Reference Tiling) performs deterministic spatial localization relative to the reference state.

For each tile T_i:

- Compute structured deviation magnitude S_i
- Compute largest connected component ratio $L_{cc,i}$
- Compute distributed drift metric $D_{dist,i}$

Connected components exceeding threshold τ_S form region proposals:

$$\mathcal{R}_k = \{T_i : S_i > \tau_S \}$$

These region proposals represent candidate physical state changes.

Importantly:

STRT does not classify; it localizes.

C.4 DIF as Structural Discriminator

Once region $\mathcal{R}_k$ is identified, DIF evaluates internal directional coherence.

For region $\mathcal{R}_k$:

- Mean directional coherence K_k
- Mean drift angle θ_k
- Angular variance $\sigma_{\theta,k}^2$

Interpretation:

- High K_k, low variance → physically organized instability
- Low K_k, high variance → stochastic noise

- High magnitude but low coherence → transient disturbance

DIF determines whether deviation is structurally meaningful.

C.5 Interior vs Exterior Differential Metric

For distributed perturbations (e.g., haze), the most diagnostic metric is interior–exterior contrast:

$$\Delta_{in-out} = \mu(\text{drift} \mid \mathcal{R}_{interior}) - \mu(\text{drift} \mid \mathcal{R}_{exterior})$$

This metric confirms:

- Whether interior state diverges measurably from baseline
- Whether boundary energy alone is driving detection
- Whether distributed field-level redistribution is present

This prevents edge-only overemphasis.

C.6 Adaptive Analytical Focus (AAF)

The phrase "Zoom computational attention where instability exists" is formalized as Adaptive Analytical Focus (AAF).

AAF is not a visual zoom; it is analytical refinement triggered by structured deviation.

Possible refinement actions:

1. Recursive STRT subdivision within $\mathcal{R}_k$
2. Higher-resolution drift computation
3. Increased temporal sampling (LDE integration)
4. Region-specific normalization
5. SLE overlay to isolate spectral redistribution

Selection policy depends on region topology:

Region Type	Dominant Metric	Refinement Target
Distributed interior	High D_{dist}, moderate K	Persistence + SLE
Boundary band	High L_{cc}, high gradient	Directional coherence
Localized ROI	High K, compact L_{cc}	Micro-tile subdivision

AAF therefore converts deviation into targeted measurement amplification.

C.7 LDE Integration — Temporal Conformance

STRT and DIF operate spatially and structurally.
LDE (Longitudinal Drift Engine) extends evaluation temporally.

For region $\mathcal{R}_k$:

$$LDE_k(t) = \int_{t_0}^{t} PWDF_k(\tau) \, d\tau$$

Where PWDF is persistence-weighted drift flux.

Temporal evaluation distinguishes:

- Transient fluctuation (low persistence)
- Stable redistributed film
- Accelerating instability (positive DAI_2)

Thus:

- STRT → Where
- DIF → What structure
- LDE → For how long and with what acceleration

C.8 Three-Domain Conformance Stack

The complete conformance evaluation becomes:

1. Spatial Domain (STRT)
   - Tile-level deviation localization
2. Structural Domain (DIF)
   - Directional coherence & organized drift
3. Temporal Domain (LDE + DAI)
   - Persistence & acceleration modeling

A region is declared non-conformant only when deviation is:

- Spatially localized
- Directionally coherent

- Temporally persistent

C.9 Graded Conformance Profile

Rather than binary output, the system produces a conformance vector:

$$C = (S_{mean}, L_{cc}, K, \sigma_\theta, \Delta_{in-out}, PWDF, DAI_1, DAI_2)$$

This allows process engineers to assess:

- Magnitude
- Distribution
- Organization
- Persistence
- Acceleration

This aligns directly with metrology and tolerance frameworks.

C.10 Null Result as Verified Conformance

Within State Conformance:

Absence of structured deviation is a positive result.

If after cleaning or processing:

- $S_i \to 0$
- $K \to random$
- $PWDF \to 0$
- $DAI_2 \le 0$

The system confirms restored conformance.

Under anomaly detection framing this is trivial;
under SCF this is verification.

C.11 Engineering Implications

This region-based structured conformance architecture:

- Eliminates dependency on probabilistic defect models
- Enables calibration-based operation
- Reduces training bias concerns
- Provides traceable physical metrics
- Supports recursive refinement without AI black-boxing

It also prepares the framework for:

- Field-to-object transition modeling (FOTM)
- Multi-scale recursive inspection
- Structured-light guided conformance targeting

C.12 Summary

Appendix C formalizes the transition from raw drift measurement to region-aware, structurally evaluated, temporally validated conformance analysis.

It operationalizes:

- STRT as spatial localization
- DIF as structural coherence validator
- LDE as persistence engine
- AAF as adaptive refinement mechanism

Together they form a deterministic State Conformance stack capable of confirming adherence to physical expectation or quantifying the specific topology through which conformance is lost.

Appendix D — Hierarchical State Conformance Modeling and Field-to-Object Transition

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D.1 Purpose of This Appendix

This appendix formalizes the hierarchical modeling logic that governs how distributed field-level instability transitions into object-level emergence within the State Conformance Framework (SCF).

It addresses a core question:

> At what point does structured drift cease to be a distributed field fluctuation and become a discrete physical object or defect?

The answer is not based on classification labels. It is based on measurable structural saturation across spatial, directional, and temporal domains.

D.2 Distributed Field Instability as a Pre-Object State

Most material deviations begin as distributed instability rather than discrete objects.

Examples:

- Thin-film haze before particulate formation
- PCB copper micro-variation before crack propagation
- CMP slurry redistribution before trench exposure
- Surface contamination prior to visible boundary formation

These early states are characterized by:

- Low-to-moderate magnitude drift
- Distributed topology
- Increasing directional coherence
- Growing persistence

This phase is defined as **Field-Level Instability (FLI)**.

D.3 Hierarchical Conformance Layers

The SCF hierarchy can be expressed as:

Layer 1 — Spatial Localization (STRT)

Si,Lcc,iS_i, \quad L_{cc,i}Si,Lcc,i

Identifies deviation distribution and connected topology.

Layer 2 — Structural Organization (DIF)

K,σθ2K, \quad \sigma_\theta^2K,σθ2

Measures directional coherence and vector alignment.

Layer 3 — Spectral Redistribution (SLE)

SLE(x,y)=max(0,HFref(x,y)−HFcurrent(x,y))SLE(x,y) = \max(0, HF_{ref}(x,y) - HF_{current}(x,y))SLE(x,y)=max(0,HFref(x,y)−HFcurrent(x,y))

Detects texture collapse, blur, or thin-film redistribution independent of directional edge shifts.

Layer 4 — Temporal Persistence (LDE + PWDF)

PWDF(t),LDE(t)PWDF(t), \quad LDE(t)PWDF(t),LDE(t)

Measures persistence-weighted drift accumulation.

Layer 5 — Acceleration Modeling (DAI)

DAI1=ddtPWDF(t)DAI_1 = \frac{d}{dt} PWDF(t)DAI1=dtdPWDF(t) DAI2=d2dt2PWDF(t)DAI_2 = \frac{d^2}{dt^2} PWDF(t)DAI2=dt2d2PWDF(t)

Distinguishes stable redistribution from accelerating instability buildup.

D.4 Field Saturation and Emergence Threshold

A distributed instability transitions toward object emergence when the following conditions converge:

1. **Spatial Concentration**

   Lcc↑L_{cc} \uparrowLcc↑

   Connected region stabilizes and condenses.

2. **Directional Saturation**

   K→KsatK \rightarrow K_{sat}K→Ksat

   Coherence approaches alignment ceiling.

3. **Persistence Growth**

$$PWDF(t) \uparrow$$

4. **Positive Acceleration**

   $$DAI_2 > 0$$

When these occur simultaneously within region $\mathcal{R}_k$, the system crosses a **Field-to-Object Transition Boundary (FOTB)**.

This boundary represents measurable structural emergence.

D.5 Formal Field-to-Object Transition Model (FOTM)

Let:

$$\Phi_k = w_1 S_{mean} + w_2 K + w_3 PWDF + w_4 DAI_2$$

Object emergence is declared when:

$$\Phi_k > \tau_{FOT}$$

Where:

- τ_{FOT} is a deterministic threshold calibrated under controlled reference conditions.
- w_i are physics-constrained weighting coefficients.

This model avoids classification heuristics.
It relies strictly on measurable state variables.

D.6 Distinguishing Transient Disturbance from Emergence

Transient disturbances typically exhibit:

- High instantaneous S
- Low persistence
- Low or negative DAI_2
- Low coherence stability

Thus:

$$PWDF \approx 0 \quad DAI_2 \le 0$$

The system suppresses such events via persistence weighting rather than post-hoc filtering.

This preserves determinism and reduces false escalation.

D.7 Multi-Scale Invariance

Field-to-object transition logic must remain scale-consistent.

Whether inspecting:

- 10 mm wafer region
- 1 mm PCB trace
- 100 µm micro-feature

The hierarchy remains:

Spatial → Structural → Spectral → Temporal → Acceleration

This ensures that SCF is resolution-invariant and compatible with recursive STRT tiling.

D.8 Relationship to Region-Structured Conformance (Appendix C)

Appendix C defined region-aware evaluation and adaptive analytical focus (AAF).

Appendix D extends that logic by defining what structural convergence within those regions means.

Appendix C answers:

- Where should we refine?

Appendix D answers:

- When does refinement reveal emergence?

Together they form a closed-loop system.

D.9 Engineering Interpretation

This hierarchical model reframes inspection philosophy:

Traditional paradigm:

- Detect object
- Classify defect

SCF paradigm:

- Measure distributed instability
- Quantify structural organization
- Model persistence
- Detect emergence threshold crossing

This enables:

- Earlier detection (pre-object phase)
- Quantitative instability growth modeling
- Deterministic conformance verification
- Process feedback before visible failure

D.10 Deterministic Operation

The Field-to-Object Transition Model:

- Does not require labeled defect datasets
- Does not rely on statistical anomaly priors
- Operates against defined physical baselines
- Produces traceable, interpretable metrics

This aligns with calibration-driven industrial validation procedures.

D.11 Summary

Appendix D formalizes how distributed field instability evolves into discrete object emergence within the State Conformance Framework.

It introduces:

- Hierarchical conformance layers
- Saturation-based transition logic
- Persistence-weighted modeling
- Acceleration-based emergence validation

This transforms SCF from a deviation-measurement system into a structured physical state transition engine capable of quantifying not just deviation—but the moment conformance is irreversibly lost.

If you would like next:

• I can draft **Appendix E — Experimental Validation Structure (SCF-aligned)**
• Or create a formal mathematical consolidation section combining Appendices C + D into a single theorem-style statement
• Or convert this into journal-ready formatting with figure references

Appendix E — Experimental Validation Architecture for State Conformance

---

E.1 Purpose of This Appendix

This appendix defines the experimental validation structure required to demonstrate deterministic State Conformance under controlled conditions.

Unlike anomaly-detection validation, which evaluates classification accuracy, SCF validation evaluates:

1. Baseline stability
2. Measurable structured deviation
3. Directional coherence formation
4. Spectral redistribution
5. Persistence accumulation
6. Emergence threshold crossing

Validation is therefore metric-driven, not label-driven.

E.2 Experimental Classes

Validation experiments shall be organized into four classes:

Class I — Baseline Stability Validation

Purpose: Confirm reference-state repeatability.

Class II — Distributed Field Perturbation

Purpose: Validate interior vs exterior structured deviation (e.g., thin-film haze).

Class III — Boundary-Dominant Perturbation

Purpose: Validate connected-band and directional coherence modeling.

Class IV — Emergence Escalation

Purpose: Demonstrate Field-to-Object Transition modeling under persistence growth.

E.3 Acquisition Parameters

All experiments shall document:

- Camera model and lens configuration
- Spatial resolution (px/mm)
- Illumination geometry (darkfield / structured / angle)
- Frame count per burst
- Exposure settings
- Baseline capture protocol
- Environmental stability conditions

Reference capture must precede perturbation capture.

E.4 Baseline Stability Metrics (Class I)

Baseline validation requires:

Smean≈0S_{mean} \approx 0Smean≈0 Lcc≈0L_{cc} \approx 0Lcc≈0 K→randomK \rightarrow randomK→random PWDF≈0PWDF \approx 0PWDF≈0 DAI1≈0,DAI2≤0DAI_1 \approx 0, \quad DAI_2 \le 0DAI1≈0,DAI2≤0

Repeated baseline bursts must show metric repeatability within tolerance band:

$$|S_{mean}^{(n)} - S_{mean}^{(n+1)}| < \epsilon$$

This establishes deterministic stability.

E.5 Distributed Field Validation (Class II)

Example: Thin-film or haze-style perturbation.

Required demonstrations:

1. Interior vs Exterior Contrast

$$\Delta_{in-out} > 0$$

2. Moderate Distributed Drift

$$D_{dist} \uparrow$$

3. Controlled Directional Coherence

$$K = moderate$$

4. Spectral Redistribution (SLE)

$$\mu(SLE_{interior}) > \mu(SLE_{exterior})$$

5. Persistence Growth Across Frames

$$PWDF(t) \uparrow$$

Goal: Demonstrate structured redistribution without discrete object emergence.

E.6 Boundary-Dominant Validation (Class III)

Example: Coffee-ring transition band or deposition boundary.

Required demonstrations:

1. High Connected Component Ratio

$$L_{cc} \uparrow$$

2. Elevated Directional Coherence

$$K \uparrow$$

3. Low Interior Drift (if boundary-only)

4. Stable Region Localization (STRT repeatability)

Goal: Show that SCF distinguishes edge-dominant structure from distributed haze.

E.7 Emergence Escalation Validation (Class IV)

Purpose: Validate Appendix D Field-to-Object Transition Model.

Required observations over time:

1. Increasing Spatial Concentration

Lcc(t)↑L_{cc}(t) \uparrowLcc(t)↑

2. Directional Saturation

K(t)→KsatK(t) \rightarrow K_{sat}K(t)→Ksat

3. Persistence-Weighted Drift Growth

PWDF(t)↑PWDF(t) \uparrowPWDF(t)↑

4. Positive Drift Acceleration

DAI2>0DAI_2 > 0DAI2>0

5. FOT Threshold Crossing

Φk>τFOT\Phi_k > \tau_{FOT}Φk>τFOT

This demonstrates measurable transition from distributed field instability to discrete object-level emergence.

E.8 Temporal Sampling Protocol

Each perturbation experiment shall include:

- Reference burst (10–20 frames minimum)
- Early perturbation burst
- Mid-phase burst
- Late-phase burst

Metrics must be computed per frame and aggregated via:

- Mean
- Variance

- Temporal slope
- Acceleration curve

This enables persistence and DAI modeling.

E.9 Multi-Scale Validation

Experiments shall include:

- Macro-scale region (~10–20 mm)
- Mid-scale region (~1–5 mm)
- Micro-scale ROI (sub-mm where applicable)

STRT recursive tiling shall demonstrate scale invariance.

Metrics must preserve relative ordering across scales.

E.10 Null Restoration Validation

After perturbation removal (e.g., cleaning):

Metrics must demonstrate return toward baseline:

Smean→0S_{mean} \rightarrow 0Smean→0 PWDF→0PWDF \rightarrow 0PWDF→0
DAI2≤0DAI_2 \le 0DAI2≤0 Δin−out→0\Delta_{in-out} \rightarrow 0Δin−out→0

This validates reversible conformance confirmation.

E.11 Required Artifact Outputs

Each experiment shall archive:

- Drift map images
- STRT tile overlays
- DIF vector fields
- SLE maps
- Region masks
- PWDF time plots

- DAI_1 and DAI_2 curves
- Conformance vector CCC

All outputs must be reproducible from raw acquisition.

E.12 Deterministic Validation Philosophy

Validation shall not rely on:

- Labeled defect datasets
- Probabilistic anomaly priors
- Black-box AI confidence scores

Validation shall rely exclusively on:

- Controlled baseline capture
- Structured perturbation introduction
- Quantified metric response
- Repeatable measurement behavior

This ensures calibration compatibility and metrology alignment.

E.13 Summary

Appendix E defines the experimental scaffolding required to demonstrate that:

1. SCF confirms conformance under stable conditions
2. Structured deviation is measurable and localizable
3. Directional coherence differentiates noise from physical change
4. Spectral redistribution identifies texture collapse
5. Persistence modeling suppresses transient disturbance
6. Acceleration modeling identifies emergence threshold

Together, these experiments validate the SCF as a deterministic State Conformance Engine rather than an anomaly detection system.

Appendix F — Calibration, Tolerance Bands, and Deterministic Conformance Governance

---

F.1 Purpose of This Appendix

This appendix defines how the State Conformance Framework (SCF) establishes, maintains, and governs tolerance bands for deterministic operation.

The objective is to ensure that:

1. Baseline measurements are repeatable
2. Metric thresholds are physically anchored
3. Drift sensitivity is stable across sessions
4. Escalation logic is calibration-bound, not heuristic

SCF operates as a measurement instrument, not a statistical classifier.
Calibration is therefore foundational.

F.2 Reference State Establishment Protocol

A reference state RRR must be captured under controlled conditions prior to any conformance evaluation.

Required conditions:

- Fixed optical geometry
- Fixed illumination configuration
- Stable exposure parameters
- Environmental stability window

The reference dataset shall consist of:

Nref≥10 frames (minimum)N_{ref} \ge 10 \text{ frames (minimum)}Nref≥10 frames (minimum)

From this dataset, compute baseline statistics:

μSref,σSref\mu_S^{ref}, \quad \sigma_S^{ref}μSref,σSref μKref,σKref\mu_K^{ref}, \quad \sigma_K^{ref}μKref,σKref μPWDFref,σPWDFref\mu_{PWDF}^{ref}, \quad \sigma_{PWDF}^{ref}μPWDFref,σPWDFref

These define the baseline stability envelope.

F.3 Metric Tolerance Band Definition

Each primary metric receives a tolerance band:

(1) Spatial Deviation Tolerance

$$|S_{mean}| \le \tau_S$$

Where:

$$\tau_S = \mu_S^{ref} + \alpha \sigma_S^{ref}$$

---

(2) Directional Coherence Stability Band

$$|K - \mu_K^{ref}| \le \tau_K$$

---

(3) Persistence Stability Band

$$PWDF \le \tau_{PWDF}$$

---

(4) Acceleration Stability Condition

$$DAI_2 \le 0$$

Under conformant conditions, acceleration must not remain persistently positive.

F.4 Multi-Metric Conformance Envelope

A surface is considered conformant when:

$$C = (S_{mean}, K, PWDF, DAI_1, DAI_2)$$

remains inside the calibrated tolerance envelope:

$$C \in \Omega_{cal}$$

Where Ω_{cal} is defined by tolerance bounds for each component.

This transforms conformance into a multi-dimensional bounded region rather than a binary rule.

F.5 Spectral Calibration (SLE)

For thin-film or texture-sensitive applications, SLE must also be calibrated:

$$\mu_{SLE}^{ref}, \quad \sigma_{SLE}^{ref}$$

Tolerance band:

$$SLE_{mean} \le \tau_{SLE}$$

This prevents lighting drift from falsely appearing as redistribution.

F.6 Scale-Invariant Thresholding

Tolerance bands must remain consistent across spatial scales.

If STRT recursive tiling is applied:

$$\tau_S^{(micro)} = \beta \cdot \tau_S^{(macro)}$$

Where β accounts for resolution scaling.

This ensures that:

- Micro-ROI inspection does not artificially inflate sensitivity
- Emergence thresholds remain physically grounded

F.7 Field-to-Object Transition Calibration

The Field-to-Object Transition threshold τ_{FOT} must be experimentally calibrated under controlled emergence scenarios.

Procedure:

1. Induce controlled gradual perturbation
2. Record metric evolution
3. Identify saturation point where:
    - $K \rightarrow K_{sat}$
    - $L_{cc} \uparrow$
    - $DAI_2 > 0$ sustained

Set:

$$\tau_{FOT} = \Phi_{transition}$$

This ensures emergence modeling is anchored to measurable transition events.

F.8 Drift Sensitivity Adjustment

Sensitivity tuning must occur via calibration coefficients—not arbitrary threshold editing.

Define sensitivity scalar γ:

$$S' = \gamma S \quad PWDF' = \gamma PWDF$$

Changes to γ must be logged and version-controlled.

F.9 Environmental Drift Monitoring

Long-term deployment requires detection of calibration drift.

Monitor:

$$\Delta_{cal}(t) = | \mu_S^{ref}(t) - \mu_S^{ref}(t_0) |$$

If calibration drift exceeds limit:

$$\Delta_{cal}(t) > \delta_{max}$$

Re-calibration is required.

This protects against:

- Illumination aging
- Sensor degradation
- Optical alignment shift

F.10 Deterministic Escalation Governance

Escalation from “conformant” to “non-conformant” must satisfy:

1. Exceed tolerance band
2. Persist beyond minimum time window
3. Exhibit structural coherence (DIF validation)

Formally:

$$S > \tau_S \quad \land \quad PWDF > \tau_{PWDF} \quad \land \quad K > \tau_K \quad \land \quad DAI_2 > 0$$

This multi-condition gating prevents transient false escalation.

F.11 Restoration Confirmation Criteria

After corrective action:

$$S \rightarrow 0 \quad PWDF \rightarrow 0 \quad DAI_2 \le 0 \quad \Delta_{in-out} \rightarrow 0$$

Conformance restoration must re-enter calibrated envelope Ω_{cal}.

F.12 Documentation & Traceability Requirements

Calibration events must log:

- Date/time
- Optical configuration
- Threshold values
- Sensitivity scalar γ
- Reference dataset checksum

This ensures auditability.

F.13 Alignment with Industrial QA

Calibration and tolerance governance align SCF with:

- Specification-driven QA
- Tolerance band inspection
- Process control charts
- Metrology validation

The system thus functions as:

A deterministic conformance measurement instrument.

F.14 Summary

Appendix F formalizes:

- Reference-state calibration
- Multi-metric tolerance envelopes
- Emergence threshold anchoring
- Sensitivity governance
- Environmental drift protection
- Deterministic escalation rules

Together with Appendices C–E, this completes the operational definition of the State Conformance Framework as a calibration-governed, region-aware, structurally validated, temporally modeled verification engine.

Appendix G — State Conformance Theorem and Formal Proof Sketch

---

G.1 Purpose of This Appendix

This appendix formalizes the State Conformance Framework (SCF) as a deterministic verification system governed by measurable physical quantities.

It provides:

1. A formal statement of the State Conformance Theorem
2. Explicit assumptions
3. Boundary conditions
4. A structured proof sketch
5. Non-limitation clarification

This appendix unifies:

- Appendix C — Region-Structured Conformance
- Appendix D — Field-to-Object Transition Modeling
- Appendix E — Experimental Validation Architecture
- Appendix F — Calibration & Tolerance Governance

G.2 Definitions

Let:

- RRR be a defined reference physical state.
- O(x,y,t)O(x,y,t)O(x,y,t) be an observed state.
- D(x,y,t)D(x,y,t)D(x,y,t) be the drift field derived from PASDE.
- SiS_iSi be structured spatial deviation (STRT).
- KKK be directional coherence (DIF).
- SLESLESLE be spectral redistribution.
- PWDF(t)PWDF(t)PWDF(t) be persistence-weighted drift flux.
- DAI1,DAI2DAI_1, DAI_2DAI1,DAI2 be first and second temporal derivatives.
- Ωcal\Omega_{cal}Ωcal be the calibrated conformance envelope.

G.3 State Conformance Theorem

Theorem (Deterministic State Conformance)

Given:

1. A calibrated reference state RRR,
2. A deterministic drift extraction operator,
3. A calibrated tolerance envelope Ωcal\Omega_{cal}Ωcal,

Then the observed state OOO is conformant if and only if:

C(O)   ΩcalC(O) \in \Omega_{cal}C(O)   Ωcal

Where:

$C(O) = (S_{mean}, L_{cc}, K, SLE, PWDF, DAI_1, DAI_2)$

If any component persistently exceeds calibrated tolerance bounds and exhibits directional coherence and positive acceleration, then conformance is lost.

G.4 Field-to-Object Emergence Corollary

If, within a spatial region $\mathcal{R}_k$:

1. $L_{cc} \uparrow$
2. $K \rightarrow K_{sat}$
3. $PWDF(t) \uparrow$
4. $DAI_2 > 0$ sustained

Then the system crosses a Field-to-Object Transition Boundary τ_{FOT}, and the distributed field instability transitions into discrete object emergence.

G.5 Assumptions

The theorem holds under the following assumptions:

1. Illumination stability within tolerance limits
2. Optical configuration invariance during acquisition
3. Calibration envelope established prior to evaluation
4. Drift operator deterministic and repeatable
5. Environmental perturbations within controlled range

G.6 Boundary Conditions

The theorem does not apply when:

- Optical geometry changes between reference and observation
- Sensor noise exceeds calibration envelope
- Environmental disturbances invalidate baseline
- Reference state is improperly defined

In such cases, recalibration is required.

G.7 Proof Sketch

Step 1 — Deterministic Drift Extraction

Given fixed optical geometry and illumination, PASDE yields repeatable drift field D(x,y,t)D(x,y,t)D(x,y,t).

Thus:

O=R⇒D≈0O = R \Rightarrow D \approx 0O=R⇒D≈0

Step 2 — Spatial Localization (STRT)

If deviation exists, STRT partitions and localizes:

Si>τSS_i > \tau_SSi>τS

Connected components define candidate regions.

Step 3 — Structural Coherence Validation (DIF)

Noise exhibits random directional distribution:

K≈randomK \approx randomK≈random

Physical instability exhibits coherent alignment:

K↑K \uparrowK↑

Thus structured deviation is distinguishable from stochastic fluctuation.

Step 4 — Spectral Redistribution Validation (SLE)

Texture collapse produces measurable high-frequency attenuation:

SLE>0SLE > 0SLE>0

This isolates thin-film redistribution from simple edge displacement.

Step 5 — Temporal Persistence (LDE + PWDF)

Transient disturbances decay:

PWDF→0PWDF \rightarrow 0PWDF→0

Persistent instability accumulates:

PWDF(t)↑PWDF(t) \uparrowPWDF(t)↑

Step 6 — Acceleration Modeling (DAI)

Emergent instability exhibits positive acceleration:

DAI2>0DAI_2 > 0DAI2>0

Stable redistribution does not sustain positive acceleration.

Step 7 — Conformance Determination

If all metrics remain inside Ωcal\Omega_{cal}Ωcal, conformance holds.

If metrics exceed tolerance, persist, and accelerate, conformance is deterministically lost.

G.8 Deterministic vs Probabilistic Systems

Unlike probabilistic anomaly detection:

- No defect training dataset is required.
- No posterior probability is computed.
- No learned class boundary is used.

SCF operates via calibrated physical measurement thresholds.

Thus:

State Conformance is measurement-based verification, not statistical inference.

G.9 Multi-Scale Invariance

Let inspection scale vary by factor λ\lambdaλ.

If STRT recursion and DIF vector quantization scale proportionally, then:

Cλ(O)→C(O)C_\lambda(O) \rightarrow C(O)Cλ(O)→C(O)

Therefore, conformance determination remains scale-consistent.

G.10 Null Result Validity

If after perturbation removal:

S→0S \rightarrow 0S→0 PWDF→0PWDF \rightarrow 0PWDF→0 DAI2≤0DAI_2 \le 0DAI2≤0

Then:

C(O)   ΩcalC(O) \in \Omega_{cal}C(O)   Ωcal

Conformance restoration is verifiable.

G.11 Non-Limitation Clause

The mathematical expressions herein are representative embodiments.

Alternative weighting schemes, norm selections, vector aggregation methods, or persistence functions may be employed without departing from the scope of deterministic state conformance principles.

G.12 Summary

Appendix G establishes that:

1. State Conformance is formally definable.
2. Conformance is a bounded multi-metric condition.
3. Emergence is detectable through structured saturation and acceleration.
4. Deterministic calibration governs all escalation.
5. SCF operates as a physics-anchored verification system rather than an anomaly classifier.

This completes the formalization of the State Conformance Framework as a mathematically grounded, calibration-bound, deterministic conformance engine.

Appendix H — Practical Deployment, Edge Integration, and Industrial Workflow Alignment

---

H.1 Purpose of This Appendix

This appendix defines how the State Conformance Framework (SCF) is deployed in real-world environments.

It addresses:

1. Edge vs centralized processing architecture
2. Real-time operation constraints
3. Integration with industrial QA systems
4. Deployment stability and recalibration protocols
5. Data governance and auditability
6. Escalation workflows

SCF is designed as a deterministic, calibration-bound conformance engine and must operate reliably under industrial constraints.

H.2 Edge Processing Architecture

H.2.1 Rationale for Edge Operation

SCF processes:

- Drift maps
- Vector fields
- Persistence-weighted flux
- Temporal derivatives

These operations are:

- Deterministic
- Computationally bounded
- Resolution-scalable

Because SCF does not require cloud-based model inference, it is well-suited for:

- Embedded industrial PCs
- FPGA/SoC platforms
- On-machine inspection modules

Edge deployment ensures:

- Low latency
- Deterministic timing
- No cloud dependency
- Reduced cybersecurity surface

H.3 Real-Time Operation Model

SCF can operate in:

Mode 1 — Snapshot Validation

Single-frame conformance confirmation.

Mode 2 — Burst Validation

Short sequence (10–20 frames) for persistence confirmation.

Mode 3 — Continuous Monitoring

Rolling temporal integration for early instability detection.

Real-time constraints are governed by:

$$T_{compute} < T_{acquisition}$$

Where processing latency must remain below frame acquisition interval.

H.4 Integration into Industrial QA Workflows

SCF aligns naturally with:

- Specification-based QA
- Tolerance band inspection

- SPC (Statistical Process Control) dashboards
- Inline process monitoring

Rather than replacing existing inspection systems, SCF functions as:

A deterministic conformance verification layer.

It can operate:

- Pre-object (early instability detection)
- Post-object (verification of known defect regions)
- As second-opinion validation alongside CNN-based AOI

H.5 Data Interfaces

SCF produces structured outputs:

- Conformance vector CCC
- Region masks
- DIF vector summaries
- PWDF time series
- DAI acceleration curves

Outputs can be serialized as:

- JSON
- CSV
- Binary telemetry packets

Integration pathways:

- REST API endpoints
- OPC-UA industrial interfaces
- PLC signal outputs
- MES system feeds

H.6 Escalation Workflow Integration

Industrial escalation logic can be structured as:

1. **Level 0 — Conformant**

   $C \in \Omega_{cal}$

2. **Level 1 — Early Drift Warning**

   $S > \tau_S \quad \land \quad PWDF \uparrow$

3. **Level 2 — Structured Instability**

   $K \uparrow \quad \land \quad DAI_2 > 0$

4. **Level 3 — Field-to-Object Transition**

   $\Phi_k > \tau_{FOT}$

Each escalation stage can trigger:

- Alert logging
- Process hold
- Automated imaging zoom
- Operator review

H.7 Deployment Stability Considerations

H.7.1 Optical Locking

SCF requires:

- Fixed lens position
- Fixed illumination geometry
- Controlled mounting vibration

Mechanical drift must remain within calibrated tolerance.

H.7.2 Environmental Control

Environmental variables:

- Temperature
- Humidity

- Airborne contamination

Must remain inside pre-defined operational envelope.

Deviation beyond envelope triggers recalibration requirement.

H.8 Calibration Lifecycle in Deployment

Deployment requires:

1. Initial calibration
2. Periodic baseline validation
3. Drift monitoring
4. Recalibration trigger thresholds

Automated calibration health metric:

$$\Delta_{cal}(t) = | \mu_S^{ref}(t) - \mu_S^{ref}(t_0) |$$

If:

$$\Delta_{cal}(t) > \delta_{max}$$

System enters maintenance mode.

H.9 Scalability Considerations

SCF scales along three axes:

(1) Resolution Scaling

Higher-resolution sensors increase spatial sensitivity.

(2) Computational Scaling

Recursive STRT refinement enables targeted high-resolution processing only where required.

(3) Multi-Node Scaling

Multiple cameras may feed distributed PASDE nodes with aggregated conformance vectors.

Multi-node aggregation logic:

$$C_{aggregate} = \sum_{n=1}^{N} w_n C_n$$

This enables plant-wide conformance monitoring.

H.10 Cybersecurity and Data Governance

SCF does not require cloud inference or external model updates.

Advantages:

- No model drift via remote retraining
- Reduced attack surface
- Fully on-prem deterministic operation

All calibration events and threshold modifications must be logged with:

- Timestamp
- Operator ID
- Configuration checksum

Ensuring auditability.

H.11 Coexistence with AI Systems

SCF may operate alongside:

- CNN-based AOI
- Transformer classifiers
- Defect segmentation networks

Role separation:

AI System	SCF
Object classification	State verification
Label inference	Physical deviation measurement
Probability outputs	Deterministic bounded metrics

SCF may serve as:

- Early warning layer
- Confidence validator
- Escalation gate

H.12 Field Deployment Example Scenarios

Example 1 — PCB Line

- SCF monitors distributed copper instability before crack.
- AOI flags only visible fractures.
- SCF provides pre-object instability warning.

Example 2 — Wafer CMP

- SCF detects thin-film haze redistribution.
- No discrete defect yet visible.
- Process adjustment occurs prior to yield loss.

Example 3 — Thin-Film Coating

- Interior SLE + distributed drift increase.
- Directional coherence rising.
- Preventive intervention triggered.

H.13 Deterministic Edge Advantage

Because SCF is:

- Calibration-bound
- Non-probabilistic
- Physics-anchored

It is ideal for:

- Regulated manufacturing
- Aerospace components
- Semiconductor fabrication
- High-reliability PCB production

Where deterministic behavior is required.

H.14 Summary

Appendix H formalizes the practical deployment of SCF as:

- An edge-capable conformance engine
- A calibration-governed measurement system
- A multi-level escalation workflow
- A complementary layer to AI inspection
- A deterministic industrial verification platform

This completes the SCF white paper structure by bridging mathematical formalization (Appendices C–G) with industrial operational reality.

Appendix I — Limitations, Boundary Conditions, and Future Research Directions

---

I.1 Purpose of This Appendix

This appendix clarifies:

1. Known operational limitations of the State Conformance Framework (SCF)
2. Boundary conditions under which deterministic guarantees hold
3. Sensitivity constraints
4. Open research directions
5. Areas for further empirical validation

The objective is to strengthen credibility by explicitly stating where SCF applies and where further development is required.

I.2 Optical and Illumination Dependence

SCF relies on repeatable optical scattering capture.

Limitations:

- Major illumination geometry changes invalidate baseline.
- Lens focus drift may appear as spectral redistribution (SLE).
- Sensor gain variation can alter drift magnitude.

Mitigation:

- Fixed mechanical mounts
- Calibration envelope monitoring (Appendix F)
- Periodic baseline verification

SCF assumes optical invariance during comparison.

I.3 Reference State Validity

SCF is reference-anchored.

If the reference state is:

- Poorly captured
- Already degraded
- Not representative of intended specification

Then conformance evaluation may be misleading.

Future direction:

- Multi-reference state modeling
- Adaptive baseline ensembles
- Reference lineage tracking

I.4 Extremely Low Signal-to-Noise Regimes

In extremely low-contrast conditions:

- Drift magnitude approaches sensor noise floor.
- Directional coherence estimation may become unstable.
- SLE may become illumination-sensitive.

Future work:

- Advanced denoising strategies
- Adaptive drift normalization
- Confidence weighting based on SNR estimation

I.5 Rapid Transient Phenomena

SCF emphasizes persistence modeling.

Very fast transient phenomena may:

- Occur between sampling intervals
- Escape persistence accumulation

Mitigation:

- Higher frame-rate acquisition
- Burst-mode validation
- Event-triggered capture

Future research:

- Temporal aliasing analysis
- Adaptive frame-rate control

I.6 Scale Extremes

At extreme scales:

- Macro-scale inspection may dilute micro-instability signals.
- Micro-scale inspection may amplify optical noise.

Although SCF is multi-scale invariant in theory, empirical validation across:

- Sub-100 µm features
- Multi-centimeter substrates

Remains ongoing.

I.7 Field-to-Object Threshold Calibration Sensitivity

Field-to-Object Transition thresholds τFOT\tau_{FOT}τFOT depend on empirical calibration.

Potential limitations:

- Process-dependent saturation levels
- Material-specific directional coherence ceilings
- Variation across surface types

Future work:

- Material-specific calibration libraries
- Cross-process threshold normalization

I.8 Environmental Instability

Environmental factors may influence drift signals:

- Air turbulence
- Temperature gradients
- Mechanical vibration
- Surface moisture variation

Although SCF includes calibration drift detection, dynamic environments may require:

- Environmental compensation modeling
- Sensor fusion approaches

I.9 Edge Hardware Constraints

On constrained embedded systems:

- Recursive STRT tiling depth may be limited.
- Real-time LDE accumulation may require computational optimization.

Future direction:

- FPGA-based DIF acceleration
- Quantized vector field encoding

- Hardware-accelerated PWDF integration

I.10 Non-Applicability to Non-Optical Modalities (Current Scope)

The current SCF embodiment assumes:

Electromagnetic or optical scattering inputs.

Although conceptually extensible to:

- Acoustic field mapping
- Thermal imaging
- Magnetic flux surfaces

Formal validation in these modalities is pending.

I.11 Deterministic Threshold vs Probabilistic Uncertainty

SCF is deterministic and threshold-based.

While this improves interpretability, it introduces:

- Hard boundary decisions
- Sensitivity to calibration accuracy

Future research may explore:

- Hybrid deterministic–confidence overlays
- Uncertainty bands for drift estimates

Without converting SCF into probabilistic anomaly detection.

I.12 Dataset Diversity and Generalization

Although SCF does not require labeled training data, deployment across:

- Different materials
- Different surface finishes
- Different illumination regimes

Requires baseline capture and calibration.

Future direction:

- Cross-domain calibration transfer modeling
- Meta-baseline parameterization

I.13 Longitudinal Drift Aging Effects

Over long-term deployments:

- Illumination intensity may degrade.
- Sensors may age.
- Mechanical alignment may shift.

Although Appendix F defines calibration drift detection, long-horizon modeling of:

- Gradual system aging
- Drift envelope evolution

Remains a research opportunity.

I.14 Validation Breadth

Current validation focuses on:

- PCB traces
- Thin-film redistribution
- Wafer/CMP-style haze
- Structured deposition boundaries

Future validation areas may include:

- Automotive optical surfaces
- Photonics substrates
- Coated medical devices
- High-reflectivity polished metals

I.15 Theoretical Extensions

Future theoretical research directions include:

1. Closed-form stability bounds on DAI2DAI_2DAI2
2. Formal proof of noise-directionality orthogonality
3. Topological invariants for connected component evolution
4. Spectral-phase drift decomposition models
5. Coupling SCF with adaptive optical control

I.16 Summary of Limitations

SCF is strongest when:

- Reference state is well-defined
- Optical geometry is stable
- Sampling rate matches instability evolution
- Calibration envelope is maintained

SCF is limited when:

- Optical conditions vary unpredictably
- SNR approaches sensor floor
- Extreme scale boundaries are reached
- Calibration discipline is neglected

I.17 Research Outlook

The long-term vision for SCF includes:

- Full multi-node distributed conformance networks
- Hardware-accelerated edge deployments
- Cross-material calibration transfer
- Emergence-prediction modeling before structural object formation
- Integration with process control loops

Future work will focus on expanding empirical validation breadth while preserving deterministic calibration governance.

I.18 Closing Statement

Appendix I establishes that the State Conformance Framework:

- Is deterministic but calibration-bound
- Is powerful but not universal
- Is structured but not immune to environmental constraints

By explicitly defining limitations, SCF strengthens its engineering credibility and positions itself for rigorous industrial and academic evaluation.

Appendix J — Formal State Conformance Theorem (Extended Statement and Proof Framework)

J.1 Purpose of This Appendix

Appendix G introduced the core State Conformance Theorem.
Appendix J provides a strengthened mathematical framing with:

1. Extended formal definitions
2. Explicit admissibility criteria
3. Stability constraints
4. Cross-axis reinforcement modeling
5. Boundary and sufficiency conditions
6. Proof structure refinement

This appendix elevates SCF from a structured engineering framework to a formally stated deterministic physical verification model.

J.2 Formal System Definition

Let:

- $R(x,y)$ be the calibrated reference state.
- $O(x,y,t)$ be the observed state.
- $D(x,y,t) = \mathcal{P}(R,O)$ be the deterministic drift operator.
- $\mathcal{R}_k \subset \Omega$ be region proposals from STRT.
- K_k be directional coherence within $\mathcal{R}_k$.
- SLE_k be spectral redistribution.
- $PWDF_k(t)$ be persistence-weighted drift flux.
- $DAI_{2,k}(t)$ be acceleration.

Define the conformance vector:

$$C_k(t) = (S_k, L_{cc,k}, K_k, SLE_k, PWDF_k, DAI_{1,k}, DAI_{2,k})$$

J.3 Extended State Conformance Theorem

Theorem (Structured Physical Admissibility Under SCF)

Given:

1. A calibrated tolerance envelope Ω_{cal},
2. Deterministic drift extraction $\mathcal{P}$,
3. Controlled acquisition invariance,

Then:

Conformance Condition

$$O \text{ conforms to } R \iff \forall k,\ C_k(t) \in \Omega_{cal}$$

Non-Conformance Condition

Conformance is deterministically lost if there exists a region $\mathcal{R}_k$ such that:

1. $S_k > \tau_S$

2. $K_k > \tau_K$
3. $PWDF_k(t) > \tau_{PWDF}$
4. $DAI_{2,k}(t) > 0$ sustained

This combination constitutes structured physical divergence.

J.4 Cross-Axis Reinforcement Principle

A central refinement of SCF is **cross-axis reinforcement**.

Deviation must be reinforced across at least two independent domains:

1. Spatial (STRT metrics)
2. Directional (DIF coherence)
3. Spectral (SLE redistribution)
4. Temporal (LDE persistence)

Formally:

$$\exists i,j \in \{Spatial, Directional, Spectral, Temporal\},\ i \neq j$$

such that:

$$M_i > \tau_i \quad \land \quad M_j > \tau_j$$

Single-axis deviation does not constitute admissible physical transition.

This prevents false escalation due to:

- Noise spikes
- Illumination flicker
- Single-frame artifacts

J.5 Sufficiency and Necessity Clarification

Necessary Condition for Non-Conformance

At minimum:

$$S_k > \tau_S$$

Spatial deviation must exist.

Sufficient Condition for Emergence

$$S_k > \tau_S \land K_k > \tau_K \land PWDF_k > \tau_{PWDF} \land DAI_{2,k} > 0$$

Sufficiency requires multi-axis reinforcement.

J.6 Stability Constraint

Under stable conformant conditions:

$$E[S_k] \rightarrow 0 \quad E[PWDF_k] \rightarrow 0 \quad E[DAI_{2,k}] \le 0$$

Expectation operators ensure tolerance band robustness across repeated sampling.

J.7 Field-to-Object Transition Formalization

Define the emergence functional:

$$\Phi_k(t) = w_1 S_k + w_2 K_k + w_3 PWDF_k + w_4 DAI_{2,k}$$

Object-level emergence occurs when:

$$\Phi_k(t) > \tau_{FOT}$$

Where:

- τ_{FOT} is calibrated.
- w_i are bounded and physically constrained.

This formalizes Appendix D in theorem form.

J.8 Proof Framework (Sketch)

Step 1 — Deterministic Drift Extraction

Given acquisition invariance:

$$R = O \Rightarrow D = 0$$

Thus conformant states lie within tolerance envelope.

Step 2 — Noise Orthogonality

Random noise produces:

$K_k \approx random$

Directional coherence requires structured gradient alignment.

Thus noise fails cross-axis reinforcement condition.

Step 3 — Spectral Redistribution Independence

SLE measures high-frequency attenuation independent of vector alignment.

Thus spectral and directional axes are not redundant.

Step 4 — Temporal Accumulation Discrimination

Transient perturbations:

$PWDF_k \rightarrow 0$

Emergent instability:

$PWDF_k(t) \uparrow$

Acceleration condition further separates gradual emergence from stable redistribution.

Step 5 — Multi-Axis Convergence

Only when spatial, directional, spectral, and temporal domains reinforce does divergence become admissible under SCF.

Thus:

Structured physical divergence is distinguishable from stochastic variation.

J.9 Bounded Determinism

SCF guarantees determinism only within calibrated domain:

$\Omega_{operational}$

Outside:

- Optical shifts
- Environmental disturbances
- Sensor instability

Require recalibration.

Determinism is bounded but strict within envelope.

J.10 Scale-Invariance Lemma

If spatial partitioning scales by factor λ and drift operator resolution scales proportionally, then:

$$C_k^{(\lambda)} \sim C_k$$

Thus conformance decision is invariant under resolution-preserving transformations.

J.11 Non-Reduction to Probabilistic Classification

SCF does not compute:

$$P(\text{defect} \mid O)$$

Instead it evaluates:

$$O \in \Omega_{cal}$$

This is membership testing in a bounded metric space, not posterior inference.

J.12 Mathematical Non-Limitation

The specific forms of:

- Persistence weighting
- Vector aggregation
- Spectral operator
- Acceleration modeling

Are representative embodiments.

Any mathematically equivalent formulation preserving:

- Deterministic drift extraction
- Cross-axis reinforcement
- Calibration-bound tolerance governance

Falls within SCF principles.

J.13 Concluding Statement

Appendix J formalizes SCF as a deterministic admissibility model governed by:

- Multi-axis reinforcement
- Structured spatial localization
- Directional coherence
- Spectral redistribution
- Temporal persistence
- Acceleration thresholds

It establishes that:

State Conformance is not anomaly probability.

It is bounded membership in a calibrated multi-metric physical state space.