PROVISIONAL PATENT APPLICATION

United States Patent and Trademark Office

Title of Invention:
METHOD AND SYSTEM FOR MULTI-SENSOR COUPLING-WEIGHTED COHERENCE ANALYSIS FOR WEATHER EVENT PREDICTION

Inventor:
Rhet Dillard Wike
Council Hill, Oklahoma 74427

Date:
April 7, 2026

Applicant:
AIIT — Artificial Intelligence Innovation Technologies

---

1. FIELD OF THE INVENTION

This invention relates to methods and systems for predicting severe weather events, particularly tropical cyclone for

2. BACKGROUND OF THE INVENTION

Current weather prediction systems rely primarily on numerical weather prediction (NWP) models that simulate atmosphe

Existing approaches treat the atmosphere as an isolated system. They do not systematically incorporate cross-domain c

No prior art teaches the use of a coherence decay equation with coupling-weighted decoherence channels derived from m

3. SUMMARY OF THE INVENTION

The present invention provides a method for weather event prediction comprising:

(a) Computing a planetary coherence state C using the equation:

C = C_0 * exp(-alpha * gamma_eff)

where:
- C_0 is a baseline coherence value (dimensionless, normalized to 1.0)
- alpha is a sensitivity constant (empirically derived)
- gamma_eff is the effective decoherence parameter, computed as a weighted sum of decoherence channels

(b) Computing gamma_eff as:

gamma_eff = SUM_i (w_i * gamma_i)

where each gamma_i represents a decoherence channel from a distinct sensor domain, and each w_i is a coupling weight

(c) Applying coupling weights derived from physical threshold conditions, including but not limited to:
- Sea surface temperature (SST) relative to the 26.5 degrees C cyclogenesis threshold
- Wind shear magnitude
- Saharan Air Layer dust loading
- Atmospheric moisture content

(d) Computing a null event probability — the likelihood that present conditions will NOT produce an event despite ele

(e) Outputting a prediction comprising: coherence state C, event formation probability, null event probability, and t

4. DETAILED DESCRIPTION OF THE INVENTION

4.1 System Architecture

The system comprises:

1. **Multi-Domain Sensor Ingestion Layer**: Real-time data acquisition from:
   - NOAA National Weather Service (weather alerts, barometric pressure)
   - USGS Water Services (dam streamflow at 13+ major US dams)
   - NOAA Space Weather Prediction Center (Kp index, solar wind speed/density)
   - USGS Earthquake Hazards (seismic event catalog)
   - NOAA CO-OPS (coastal tide levels at 6+ stations)
   - NASA DONKI (coronal mass ejections, solar flares, geomagnetic storms)
   - FAA NOTAM system (airspace holds as atmospheric stress proxy)
   - EPA AirNow (air quality as combustion/volcanic proxy)

2. **Historical Reference Database**: Archival data comprising:
   - 1,973 Atlantic tropical storms (1851-2024, HURDAT2)
   - 34,430 daily Kp index records (1932-2024, GFZ Potsdam)
   - 47,037 M5+ earthquakes (1900-2024, USGS FDSN)
   - Daily streamflow records from 13 major US dams (2007-2024, USGS)
   - Hourly tide levels from 6 coastal stations (2015-2024, NOAA CO-OPS)

3. **Coherence Computation Engine**: Implements the coupling-weighted gamma calculation and exponential coherence dec

4. **Null Event Analyzer**: Identifies conditions matching historical non-formation events.

5. **Validation Gate (AnchorForge Protocol)**: Three-rebuttal gate system that stress-tests every predictive claim ag

4.2 The Coherence Equation

The core equation C = C_0 * exp(-alpha * gamma_eff) is derived from the physics of decoherence in coupled systems. Th

This is the central claim of the invention: weather events are coherence phenomena. A tropical cyclone forms when

Conversely, a null event occurs when one or more coupling weights approach zero, preventing energy transfer even when

4.3 Decoherence Channels (gamma_i)

Each channel is computed from sensor data as follows:

Channel 1: Geomagnetic (gamma_geo)
- Source: Kp index (SWPC), solar wind speed and density (ACE/DSCOVR)
- Computation: gamma_geo = (Kp / 9.0) * (V_sw / 800.0) where V_sw is solar wind speed in km/s
- Normalization: 0 to 1

Channel 2: Hydrological (gamma_hydro)
- Source: Dam streamflow (USGS) at 13 stations
- Computation: For each dam, compute z-score of current flow vs. historical mean. gamma_hydro = fraction of dams show
- Key finding: Pre-hurricane windows show systematic negative z-scores (reduced flow) across multiple independent riv

Channel 3: Ocean Thermal (gamma_sst) — THE COUPLING WEIGHT
- Source: SST data for Atlantic Main Development Region
- Computation: w_sst = max(0, (SST - 26.5) / 5.0), capped at 1.0
- This is not a decoherence channel but a coupling weight applied to gamma_geo. When SST < 26.5 degrees C, w_sst = 0
- **Validated**: 267 null events analyzed. November accounts for 35.6% of nulls vs. 4.8% of formations (7.42x overrep

Channel 4: Tidal (gamma_tide)
- Source: Hourly tide levels at 6 coastal stations (NOAA CO-OPS)
- Computation: gamma_tide = max deviation from predicted tide / mean tidal range
- Indicates gravitational stress and storm surge precursors

Channel 5: Seismic (gamma_seismic)
- Source: USGS earthquake catalog
- Computation: gamma_seismic = log10(cumulative moment release in 7 days) / 25.0, normalized
- Monthly correlation with Kp (r = 0.648) suggests shared seasonal driver but independent energy release

Channel 6: Atmospheric (gamma_atm)
- Source: Weather alerts (NWS), barometric pressure, AQI
- Computation: gamma_atm = weighted count of active severe weather alerts in monitored regions

Channel 7: Barometric (gamma_baro)
- Source: NWS observation stations
- Computation: gamma_baro = |dP/dt| / 5.0 where dP/dt is pressure change rate in mb/hr

4.4 Null Event Analysis — The Key Innovation

The most novel aspect of this invention is the systematic use of null events — cases where conditions appeared favora

Method:
1. From the historical database, identify all time windows during which one or more decoherence channels exceeded thr
2. Classify each window as "formation" (a tropical system formed within 14 days) or "null" (no formation)
3. For each null event, identify which coupling weight(s) were suppressed (e.g., SST below threshold, high wind shear
4. Build a null event profile: the statistical distribution of suppression channels across all null events
5. For real-time prediction: compare current sensor state against the null event profile. If the current state matche

Empirical validation:
- 267 null events identified in the 1932-2024 Kp/hurricane overlap
- Null events cluster in November (35.6%) and June (early season, low SST)
- Formation events cluster in September (35.4%) — peak SST season
- The SST coupling weight alone explains 85%+ of the formation/null separation

4.5 Cross-System Teleconnection Detection

The system identifies teleconnections — remote correlations between physically separated sensor systems — that serve

Example: Columbia River Teleconnection
- Grand Coulee Dam and Bonneville Dam streamflow correlation: r = 0.79
- When both dams simultaneously show anomalous flow (|z| > 2.0), Gulf of Mexico hurricane formation occurs within 30
- Mechanism: jet stream waveguide connects Pacific Northwest hydrology to Atlantic cyclogenesis conditions (PNA patte
- Sample size: 10 events (marginal, requires additional data collection for confirmation)

4.6 Self-Correcting Validation (AnchorForge Protocol)

Every predictive claim generated by the system passes through a three-rebuttal gate before output:

- **Gate A (Data)**: Is the underlying data statistically sound? Is the baseline calculation correct? Is the sample s
- **Gate B (Scope)**: Does the claim generalize beyond the training data? Are confounders controlled?
- **Gate C (Source)**: Is the methodology sound? Are there known alternative explanations?

Gate scoring: 3/3 pass = gate multiplier 1.0 (full confidence), 2/3 = 0.7 (marginal), 0-1/3 = 0.0 (killed). Claims th

Demonstrated capability: The system's initial analysis produced a 4.6x enrichment claim for Kp-hurricane correlat

5. CLAIMS

Claim 1. A method for predicting weather events comprising:
(a) receiving real-time sensor data from a plurality of physically distinct sensor domains including at least two of:
(b) computing a decoherence parameter gamma_i for each sensor domain;
(c) computing a coupling weight w_i for at least one sensor domain based on a physical threshold condition;
(d) computing an effective decoherence parameter gamma_eff as a weighted sum of the decoherence parameters;
(e) computing a coherence state C using the equation C = C_0 * exp(-alpha * gamma_eff);
(f) comparing the coherence state against a historical database of formation events and null events; and
(g) outputting a weather event prediction comprising at least an event formation probability and a null event probabi

Claim 2. The method of Claim 1, wherein the coupling weight for ocean thermal coupling is computed as w_sst = max

Claim 3. The method of Claim 1, wherein the null event probability is computed by comparing the current sensor st

Claim 4. The method of Claim 3, wherein the null event profile identifies which coupling weight(s) were suppresse

Claim 5. The method of Claim 1, further comprising detecting cross-system teleconnections by computing time-lagge

Claim 6. The method of Claim 5, wherein a hydrological teleconnection is detected when anomalous streamflow at tw

Claim 7. The method of Claim 1, further comprising a self-correcting validation gate that subjects each predictiv

Claim 8. A system for weather event prediction comprising:
(a) a sensor ingestion module configured to receive real-time data from a plurality of sensor domains;
(b) a coherence computation engine configured to compute coupling-weighted decoherence parameters and a coherence sta
(c) a null event analyzer configured to compare current conditions against a database of historical null events;
(d) a validation gate configured to stress-test predictive claims before output; and
(e) a prediction output module configured to deliver formation probability, null event probability, and dominant coup

Claim 9. The system of Claim 8, wherein the sensor domains comprise at least: USGS dam streamflow data, NOAA spac

Claim 10. The system of Claim 8, wherein the coherence computation engine applies the equation C = C_0 * exp(-alp

Claim 11. A computer-implemented method for identifying weather event suppression conditions, comprising:
(a) receiving historical records of weather events and associated multi-domain sensor data;
(b) identifying time windows in which at least one decoherence channel exceeded a formation threshold but no weather
(c) for each such null event, determining which coupling weight(s) were below a coupling threshold;
(d) computing a null event profile comprising the statistical distribution of suppressed coupling channels; and
(e) using the null event profile to predict suppression of future weather events when current sensor data matches the

Claim 12. The method of Claim 11, wherein the coupling threshold for tropical cyclone prediction is a sea surface

6. ABSTRACT

A method and system for predicting weather events using coupling-weighted multi-sensor coherence analysis. The system

7. RETROACTIVE VALIDATION

7.1 Data and Protocol

The calibrated multi-factor model was validated against 38 Atlantic hurricane seasons (1982-2023, excluding 1993-1996

- **SST anomaly** above the 26.5 degrees C cyclogenesis threshold in the Atlantic Main Development Region (MDR: 10-20
- **ENSO modulation** from NOAA CPC ONI values (ASO quarter), representing La Nina enhancement and El Nino suppressio
- **Geomagnetic activity** from GFZ Potsdam Kp archive (June-November seasonal average), representing solar-terrestri

Calibrated formation score = SST_anomaly * 4.0 + ENSO_term * 7.0 + (1 - Kp/9) * (-0.5) + (-2.0)

Weights were determined by grid search and hill-climbing optimization over the 38-season training set, maximizing a c

The target variable was observed seasonal named storm count from the HURDAT2 database (1,973 storms, 1851-2024).

7.2 Results

Primary metric — Spearman rank correlation:

In retrospective validation across 38 Atlantic hurricane seasons (1982-2023), the calibrated multi-factor model achie

Bootstrap confidence intervals (10,000 resamples):
- Multi-factor model: rho = 0.706, 95% CI [0.434, 0.845]
- SST alone: rho = 0.497, 95% CI [0.137, 0.713]

Robustness under resampling:
- Leave-one-out Spearman: mean rho = 0.706, range [0.682, 0.766]
- 5-fold cross-validation: mean rho = 0.686 (folds: 0.893, 0.857, 0.821, 0.357, 0.500)

Variance explained:
- Multi-factor model: rho-squared = 0.498 (explains 49.8% of seasonal rank variance)
- SST alone: rho-squared = 0.247 (explains 24.7% of seasonal rank variance)
- The multi-factor model explains 2.02x more seasonal variance than SST alone.

Decile separation:
- Top-decile predictions (10 highest-scoring seasons): mean 20.7 storms, 95% CI [17.4, 24.5]
- Bottom-decile predictions (10 lowest-scoring seasons): mean 11.7 storms, 95% CI [9.5, 14.1]
- Confidence intervals do not overlap. Separation ratio: 1.77x.

Reliability curve (quartile binning):

Quartile	Score Range	Mean Storms	N
Q1 (lowest)	[-2.7, -0.1]	11.9	9
Q2	[-0.1, 2.0]	12.9	9
Q3	[2.0, 3.3]	18.1	9
Q4 (highest)	[3.5, 5.1]	20.9	9

The relationship is monotonically increasing across all four quartiles.

7.3 Notable Predictions

- **2010**: Model score 7.60 (highest in dataset). Actual: 21 storms, HYPERACTIVE. La Nina + 28.2C SST produced the m
- **2020**: Model score 4.92. Actual: 31 storms (record-breaking). Correctly placed in top decile.
- **2015**: Model score 0.64 (NORMAL). Actual: 12 storms (NORMAL). Despite record Atlantic SST of 28.0C, strong El Ni
- **2023**: Model score 5.12. Actual: 21 storms, HYPERACTIVE. Correctly identified despite El Nino conditions, becaus

7.4 Permutation Test

Permutation testing (100,000 shuffles) yielded p approximately equal to 1 x 10^-5, indicating that the observed rank

No evidence of overfitting under LOO and cross-validation, though sample size (n=38) remains a constraint. Forward pr

7.5 Residual Misses

5 of 38 seasons (13.2%) show prediction error exceeding one activity category:
- 1984, 1985, 1986, 1987: Low SST (26.7-27.6C) combined with El Nino or neutral ENSO produces low model scores, but o
- 2002: El Nino year (ONI = +1.01) where the model over-penalized ENSO suppression.

All 5 misses involve the model underpredicting activity in the 1980s or during El Nino conditions, suggesting a syste

7.6 Calibrated Weights — Physical Interpretation

Parameter	Weight	Interpretation
SST anomaly above 26.5C	4.0	Primary driver — each degree above threshold adds 4.0 to formation score
ENSO term	7.0	Strongest modifier — La Nina enhances, El Nino suppresses formation potential at 1.75x the weight
Geomagnetic (Kp)	-0.5	Empirically observed weak inverse modifier — higher Kp slightly reduces formation score
Bias	-2.0	Baseline offset ensuring quiescent conditions score below zero

The dominant weights (SST anomaly and ENSO) align with established tropical meteorology. The Kp term is an empiricall

7.7 Limitations and Non-Causality Statement

The model identifies statistical relationships and does not assert causal mechanisms beyond established physical driv

8. DRAWINGS

FIG. 1 — System Architecture Diagram. Shows the multi-domain sensor ingestion layer (SST, ENSO, Kp, Wind Shear, M

FIG. 2 — 38-Season Retroactive Validation Scatter Plot. Model formation score (x-axis) versus observed Atlantic n

FIG. 3 — Reliability Curve (Quartile Calibration). Bar chart showing mean observed storm count per model score qu

FIG. 4 — Sigmoid SST Coupling Weight Function. Plot of w_sst = 1/(1+exp(-k*(SST-26.5))) for SST range 24-30 degre

See attached: PATENT_FIGURES/ (4 PDF sheets) and PATENT_CODE_APPENDIX.md (3 code listings).

Filing Notes:
- Filing fee: $320 (micro entity)
- File via USPTO EFS-Web or patent center
- This provisional establishes priority date; non-provisional must be filed within 12 months
- No claims examination for provisional — claims included here to establish scope for non-provisional conversion
- Recommended: file as micro entity (annual gross income < $228,756, not named on > 4 previous US patents)

Supporting Data (available upon request):
- RETROACTIVE_VALIDATION.json — full 38-season retroactive validation results
- CALIBRATION_V1.json — calibrated weights, thresholds, and metrics
- sst_monthly_mdr.json — 448 monthly MDR SST records (NOAA OISST v2.1)
- enso_history.json — 76 seasons of ENSO ONI values (1950-2025)
- ANCHORFORGE_V5_GATE_RESULTS.json — validation results for all claims
- NULL_EVENT_ANALYSIS.json — full null event analysis
- CROSS_SYSTEM_DEEP.json — cross-system correlation data
- KP_HURRICANE_DEEP.json — dose-response and lag analysis
- MASTER_CORRELATION.json — master correlation report
- hurricanes.json — 1,973 Atlantic storms (HURDAT2, 1851-2024)
- kp_archive.json — 34,430 daily Kp records (GFZ Potsdam, 1932-2024)
- 384,000+ historical sensor records across 5 domains