Systematic Absence of Low-Confidence Nighttime Fire Detections in VIIRS Active Fire Product: Evidence of Undocumented Algorithmic Filtering

Rohit Rajendra Dhage[1*]

[1]Independent Researcher

[*]Corresponding author: rohitdhage13881@gmail.com

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Abstract

The Visible Infrared Imaging Radiometer Suite (VIIRS) active fire product is widely used for global fire monitoring, yet its confidence classification scheme exhibits an undocumented systematic pattern. Through analysis of 21,540,921 fire detections spanning one year (January 2023 - January 2024), I demonstrate a complete absence of low-confidence classifications during nighttime observations. Of 6,007,831 nighttime fires, zero were classified as low confidence, compared to an expected 696,908 under statistical independence ($\chi^2 = 1,474,795$, $p < 10^{-15}$, $Z = -833$). This pattern persists globally across all months, latitude bands, and both NOAA-20 and Suomi-NPP satellites. Machine learning reverse-engineering (88.9% accuracy), bootstrap simulation (1,000 iterations), and spatial-temporal analysis confirm this is an algorithmic constraint rather than a geophysical phenomenon. Brightness temperature analysis reveals nighttime fires below approximately 295K are likely excluded entirely rather than flagged as low-confidence, while daytime fires show normal confidence distributions. This undocumented behavior affects 27.9% of all VIIRS fire detections and has significant implications for fire risk assessment, day-night detection comparisons, confidence-weighted analyses, and any research treating confidence levels as uncertainty metrics. I recommend explicit documentation of this algorithmic constraint in VIIRS user guides and reprocessing strategies for affected analyses.

Keywords: VIIRS, Active Fire Detection, Remote Sensing, Algorithm Validation, Confidence Classification, NASA FIRMS

1 Introduction

1.1 Background

The Visible Infrared Imaging Radiometer Suite (VIIRS) aboard the Suomi National Polar-orbiting Partnership (Suomi-NPP) and NOAA-20 satellites provides critical global fire monitoring capabilities with 375m spatial resolution [1]. The VIIRS active fire product assigns each detection a confidence level—high (h), nominal (n), or low (l)—intended to represent detection reliability based on brightness temperature, viewing geometry, and contextual factors [2]. These confidence metrics are fundamental to fire risk assessments, climate models, and operational fire management systems worldwide.

1.2 The Confidence Classification Problem

Confidence levels in satellite fire products serve multiple purposes: (1) filtering false alarms, (2) quantifying detection uncertainty, (3) weighting observations in statistical analyses, and (4) comparing detection quality across different conditions [3]. The VIIRS algorithm documentation indicates confidence should reflect multiple factors including brightness temperature thresholds, background characterization, and pixel classification tests, with lower confidence assigned to marginal detections [4].

However, preliminary analysis of large-scale VIIRS datasets revealed an unexpected pattern: nighttime observations appear to lack any low-confidence classifications. This systematic absence contradicts the assumption that confidence levels represent a continuous assessment of detection uncertainty across all observing conditions.

1.3 Research Objectives

This study investigates whether the apparent absence of low-confidence nighttime fire detections represents: (1) a true geophysical phenomenon, (2) a statistical artifact, or (3) an undocumented algorithmic constraint. I employ multiple independent validation methods including chi-square testing, machine learning reconstruction, bootstrap simulation, spatial-temporal analysis, and brightness threshold investigation to characterize this pattern and assess its implications for VIIRS data users.

2 Data and Methods

2.1 Dataset

I analyzed VIIRS active fire data obtained from NASA's Fire Information for Resource Management System (FIRMS) [5] covering the period January 17, 2023 to January 17, 2024. The dataset comprises 21,540,921 fire detections from both Suomi-NPP and NOAA-20 satellites, representing global fire activity across all biomes and fire regimes.

Each detection includes:

- Geographic coordinates (latitude, longitude)
- Brightness temperature (channel I-4, 3.74 μm)
- Acquisition date and time (UTC)
- Day/night flag (D/N)
- Confidence level (h/n/l)
- Fire Radiative Power (FRP, MW)
- Satellite and instrument identifiers
- Scan and track position

2.2 Data Quality Control

Prior to analysis, I performed comprehensive data validation (Table 1):

Table 1: Data Quality Validation Results

Check	**Result**	**Status**
Missing values	0	✓
Valid confidence values (h/n/l)	100%	✓
Valid day/night flags (D/N)	100%	✓
Geographic bounds ($-90 \leq$ lat ≤ 90)	100%	✓
Geographic bounds ($-180 \leq$ lon ≤ 180)	100%	✓
Brightness range (280-500K typical)	99.94%	✓
Sample size adequacy ($n > 10^6$)	Yes	✓

2.3 Statistical Methods

2.3.1 Chi-Square Test of Independence

I tested the null hypothesis of independence between confidence classification and day/night status using Pearson's chi-square test:

$$\chi^2 = \sum_{i,j} \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \tag{1}$$

where O_{ij} represents observed counts and E_{ij} represents expected counts under independence:

$$E_{ij} = \frac{(\text{row total}_i) \times (\text{column total}_j)}{\text{grand total}} \tag{2}$$

Standardized residuals were calculated to identify specific cells contributing to deviation:

$$Z_{ij} = \frac{O_{ij} - E_{ij}}{\sqrt{E_{ij}}} \tag{3}$$

2.3.2 Bootstrap Resampling

To assess pattern robustness, I performed 1,000 bootstrap iterations, each sampling 10,000 nighttime fires with replacement and counting low-confidence detections. This establishes empirical confidence intervals for the expected count under the observed distribution.

2.3.3 Machine Learning Reconstruction

I employed decision tree classification (scikit-learn [6]) to reverse-engineer the confidence assignment algorithm:

Algorithm 1 ML-Based Algorithm Reconstruction

1: **Input:** Features $X = \{\text{brightness, scan, track, FRP, is\_night}\}$
2: **Output:** Predicted confidence $\hat{y} \in \{h, n, l\}$
3: Split data: 80% train, 20% test (stratified by confidence)
4: Train decision tree classifier with max_depth=10
5: Evaluate on test set
6: Extract feature importances
7: Test predictions on nighttime-only subset

2.4 Spatial-Temporal Analysis

To verify the pattern's global consistency, I:

1. Divided the globe into 10×10 grid cells
2. Calculated nighttime low-confidence counts per cell
3. Performed monthly aggregation (12 months)
4. Tested pattern consistency across latitude bands

3 Results

3.1 Descriptive Statistics

The dataset exhibits the following characteristics (Table 2):

Table 2: Dataset Descriptive Statistics

Metric	**Value**
Total fire detections	21,540,921
Date range	Jan 17, 2023 - Jan 17, 2024
Daytime fires (D)	15,533,090 (72.1%)
Nighttime fires (N)	6,007,831 (27.9%)
High confidence (h)	1,112,469 (5.2%)
Nominal confidence (n)	17,938,742 (83.3%)
Low confidence (l)	2,489,710 (11.6%)
Mean brightness (day)	341.1 K
Mean brightness (night)	312.3 K

3.2 The Zero Pattern: Contingency Analysis

Table 3 presents the core finding:

Table 3: Contingency Table: Confidence Level by Day/Night Status

Confidence	**Day (D)**	**Night (N)**	**Total**
High (h)	1,046,811	65,658	1,112,469
Low (l)	2,489,710	**0**	2,489,710
Nominal (n)	11,996,569	5,942,173	17,938,742
Total	15,533,090	6,007,831	21,540,921

Key Finding: Of 6,007,831 nighttime fires, precisely **zero** were classified as low confidence.

3.3 Statistical Significance

Chi-square test results demonstrate extreme deviation from independence:

- $\chi^2 = 1,474,795.20$ (df = 2)
- $p < 10^{-15}$ (effectively zero)
- Effect size: Cramér's V = 0.262 (large effect)

Expected count under independence: $E_{l,N} = \frac{2,489,710 \times 6,007,831}{21,540,921} = 694,908$
Standardized residuals (Table 4) identify extreme deviations:

Table 4: Standardized Residuals (Z-scores)

Confidence	**Day (D)**	**Night (N)**
High (h)	+273.11	-439.15
Low (l)	+518.24	**-833.30**
Nominal (n)	-261.08	+419.80

The nighttime low-confidence cell shows a residual of $Z = -833.30$, indicating the observed value is 833 standard deviations below expectation—an astronomical statistical anomaly incompatible with random processes.

3.4 Five-Method Verification

I verified the zero count using five independent computational approaches:

Table 5: Multi-Method Verification of Zero Count

Method	**Count**	**Implementation**
Direct boolean filter	0	`df[(night) & (low)]`
Boolean sum	0	`((night) & (low)).sum()`
Crosstab lookup	0	`pd.crosstab(...)`
Value counts	0	`night['conf'].value_counts()`
SQL-style query	0	`df.query("N and l")`

Perfect agreement across all methods eliminates computational error as an explanation.

3.5 Brightness Temperature Analysis

Table 6 reveals systematic brightness thresholds:

Table 6: Brightness Temperature Statistics by Category

Category	Count	Mean (K)	Median (K)	Min (K)	Max (K)
Day-High	1,046,811	367.0	367.0	367.0	367.0
Day-Low	2,489,710	337.8	336.2	295.0	367.0
Day-Nominal	11,996,569	341.1	340.6	295.0	367.0
Night-High	65,658	367.0	367.0	367.0	367.0
Night-Low	**0**	—	—	—	—
Night-Nominal	5,942,173	312.3	308.5	295.0	367.0

Critical Observation: Daytime low-confidence fires range from 295K to 367K (mean 337.8K), while nighttime nominal-confidence fires begin at 295K (mean 312.3K). This suggests a hard brightness cutoff at approximately 295K, below which nighttime fires are discarded rather than classified as low-confidence.

3.6 Temporal Consistency

The pattern holds across all 12 months without exception (Table 7):

Table 7: Monthly Pattern Analysis

Month	Total Fires	Night Fires	Night Low-Conf	Pattern Holds
January	1,629,853	483,029	0	Yes
February	1,596,874	471,283	0	Yes
March	1,439,323	424,896	0	Yes
April	1,380,119	407,235	0	Yes
May	1,421,932	419,771	0	Yes
June	1,490,660	440,095	0	Yes
July	2,152,563	635,756	0	Yes
August	2,940,953	868,681	0	Yes
September	2,589,561	764,368	0	Yes
October	2,135,937	630,152	0	Yes
November	1,360,597	401,576	0	Yes
December	1,402,549	414,453	0	Yes
Total	21,540,921	6,007,831	**0**	**100%**

3.7 Spatial Consistency

Analysis of 15 latitude bands (each with > 100 fires) shows universal pattern adherence. Of regions analyzed, 15/15 (100%) exhibit zero nighttime low-confidence fires, confirming this is a global algorithmic constraint rather than regional artifact.

3.8 Machine Learning Reconstruction

Decision tree classification achieved 88.9% accuracy in predicting confidence levels from physical parameters:

Table 8: Machine Learning Model Performance

Metric	Value
Test accuracy	0.889
Training samples	17,232,736
Test samples	4,308,185
Model type	Decision Tree (depth=10)

Feature importance analysis:

1. Brightness temperature: 82.8%
2. Day/night flag: 8.7%
3. Track position: 6.0%
4. Fire Radiative Power: 2.4%
5. Scan position: 0.1%

Critical Test: When predicting confidence for 1,202,637 nighttime test fires, the model predicted **zero** as low-confidence—successfully learning the algorithmic constraint.

3.9 Bootstrap Validation

Across 1,000 bootstrap iterations (each sampling 10,000 nighttime fires with replacement):

- Mean low-confidence count: 0.00
- Standard deviation: 0.00
- Minimum: 0
- Maximum: 0
- 95% CI: [0, 0]

The bootstrap distribution is degenerate (single point mass at zero), confirming the pattern is deterministic, not stochastic.

4 Discussion

4.1 Algorithmic Interpretation

The evidence collectively points to an undocumented algorithmic constraint in VIIRS fire detection. I propose the following decision logic based on empirical findings:

Algorithm 2 Inferred VIIRS Confidence Assignment (Simplified)

if brightness $< \theta_{\text{min}}$ **then**
  reject detection {No output}
else if day/night = N **and** brightness $< \theta_{\text{night}}$ **then**
  reject detection {Explains zero low-conf}
else if brightness $\geq \theta_{\text{high}}$ **then**
  return confidence = high
else if day/night = N **then**
  return confidence = nominal {Never low}
else
  Apply multi-threshold test
  return confidence $\in$ {high, nominal, low}
end if

Brightness analysis suggests $\theta_{\text{night}} \approx 295$K, below which nighttime detections are suppressed entirely.

4.2 Comparison with MODIS

Previous studies of MODIS active fire data [3] report low-confidence nighttime fires, suggesting this constraint is VIIRS-specific rather than universal to thermal fire detection. This difference may relate to:

1. Higher spatial resolution of VIIRS (375m vs 1km)
2. Different contextual test implementations
3. Stricter false-alarm rejection for nighttime data

4.3 Physical Justification

The algorithmic constraint may reflect legitimate concerns about nighttime false alarms. At night:

- Background thermal characterization is more challenging
- Urban heat sources (streetlights, industrial facilities) create confusion
- Gas flares and other persistent thermal anomalies are more prominent
- Lower overall brightness makes marginal fires harder to distinguish from noise

However, these concerns do not justify *complete elimination* of a confidence category: Low-confidence detections exist precisely to flag uncertain cases for user evaluation.

4.4 Implications for Data Users

This undocumented behavior has several critical implications:

4.4.1 Fire Risk Assessment

Studies using confidence levels to weight fire risk underestimate nighttime uncertainty. A fire that would be classified as "low confidence" during the day is either (a) rejected entirely at night, or (b) promoted to "nominal confidence" despite similar uncertainty.

4.4.2 Day-Night Comparisons

Any analysis comparing day vs. night fire characteristics is confounded by systematically different confidence distributions. Reported "better nighttime detection reliability" may be an artifact of filtering rather than true performance difference.

4.4.3 Confidence-Weighted Analyses

Statistical methods that weight observations by confidence (e.g., inverse-confidence weighting) will systematically overweight nighttime observations due to absence of the low-confidence category.

4.4.4 Algorithm Benchmarking

Validation studies comparing VIIRS to ground truth may incorrectly attribute day-night performance differences to sensor characteristics rather than algorithmic filtering.

4.5 Recommended Mitigation Strategies

For ongoing research using VIIRS data:

1. **Separate day/night analyses**: Do not pool day and night observations in confidence-dependent analyses
2. **Binary confidence**: Collapse to binary (high vs. nominal+low) for day, treat nighttime separately
3. **Document limitations**: Explicitly note this constraint in methods sections
4. **Sensitivity analysis**: Test whether conclusions change when excluding nighttime data

For NASA FIRMS:

1. **Documentation**: Add explicit statement to user guides about nighttime confidence behavior
2. **Algorithm transparency**: Publish complete confidence assignment pseudocode
3. **Alternative coding**: Consider "not classified" vs. implicit rejection
4. **Reprocessing consideration**: Evaluate whether historical data should be reprocessed with updated classification

4.6 Limitations

This study has several limitations:

1. I analyze one year of data; longer time series would strengthen conclusions
2. I infer algorithm behavior empirically rather than from source code
3. I cannot definitively determine designer intent without NASA engineer consultation
4. Regional fire regimes may show different brightness distributions not captured in global aggregation

5 Conclusion

Through analysis of 21.5 million VIIRS fire detections using multiple independent statistical methods, I demonstrate conclusively that nighttime observations lack low-confidence classifications—a pattern incompatible with random processes ($Z = -833$, $p < 10^{-15}$). This algorithmic constraint is global, temporally consistent, and learnable by machine learning models, indicating deterministic filtering rather than geophysical causation.

The complete absence of a confidence category for 27.9% of all VIIRS fire detections has significant implications for the research community. I recommend that NASA FIRMS explicitly document this behavior in user guides and that researchers account for differential confidence distributions when comparing day and night observations or using confidence levels as uncertainty metrics.

This work demonstrates the value of large-scale empirical validation of operational satellite products. As Earth observation datasets grow larger and more complex, systematic statistical auditing becomes essential to ensure algorithms behave as intended and documented.

6 Data Availability

VIIRS active fire data are publicly available from NASA FIRMS (`https://firms.modaps.eosdis.nasa.gov/`). Analysis code is available from the author upon request.

7 Acknowledgments

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8 Conflict of Interest

The author declares no conflicts of interest.

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