

Exploring Thermal Anomalies using Continuous Wavelet Transform Approach

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Abstract

This study analyzes surface temperature time series to identify thermal anomalies to detect the strong earthquake ($M_w > 6$) on Lombok Island using the dataset from NASA satellites (LOK). We explore anomaly detection Continuous Wavelet Transform (CWT) method with a 4th-order complex Gaussian wavelet (cgau4), which allows for detailed time–frequency domain analysis. The analysis results show that NASA data only show an increase in thermal energy in 2016, which is related to the influence of El Niño, and therefore is climatological. In contrast, the LOK data shows a strong energy anomaly (dark red) in May–June 2018, which began to form in January, peaked before the earthquake, and then decreased after August 2018, coinciding with the post-earthquake period of Lombok. The differences in energy patterns between NASA and LOK indicate that pre-seismic thermal anomalies appear more prominent in the local data. Our findings indicate a possible higher sensitivity of surface observation data to changes in subsurface heat flux that indicate leading up to a seismic event. Therefore, we utilized an exploratory approach for detecting and characterizing non-stationary thermal anomalies as an early indicator of seismic activity.

Keywords:

Earthquake, Thermal, Anomaly, Detection, CWT

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1. Introduction

Thermal anomalies have long attracted scientific attention as potential indicators of geophysical processes, particularly those associated with tectonic activity and earthquake precursors. Variations in land surface temperature, infrared brightness temperature, and latent heat flux often appear before significant seismic events, suggesting complex interactions between the lithosphere, atmosphere, and ionosphere. However, these thermal signals are subtle, non-stationary, and frequently masked by seasonal variability, meteorological effects, and sensor noise. As a result, distinguishing meaningful thermal anomalies from background fluctuations remains a major challenge in geoscience research, motivating the need for advanced signal processing approaches capable of capturing transient and multi-scale characteristics in thermal datasets [9], [10], [20].

Early studies on geophysical anomalies focus primarily on geomagnetic and electromagnetic variations to understand subsurface tectonic changes. Research conducted in the Lombok Island region demonstrates that geomagnetic field anomalies correlate with local tectonic structures and seismic activity, highlighting the importance of temporal anomaly detection in complex geological settings. These works emphasize that anomaly detection requires robust analytical techniques that can separate long-term trends from short-lived disturbances. However, many traditional methods rely on linear assumptions and struggle to represent the multi-scale nature of geophysical signals, limiting their effectiveness in anomaly interpretation [1], [2], [6].

Ultra-low frequency (ULF) electromagnetic signals provide another important source of precursor information. Several studies report abnormal ULF emissions before major earthquakes, detected through polarization analysis and spectral decomposition techniques. These findings confirm that pre-seismic signals often manifest across different physical domains, including electromagnetic and thermal fields. Nevertheless, the detection of such signals remains inconsistent due to noise contamination and varying environmental conditions. This limitation underscores the necessity of time–frequency analysis methods that can localize anomalies simultaneously in time and frequency domains [3], [4], [5].

Thermal infrared anomalies derived from satellite observations emerge as a promising complementary approach for earthquake-related studies. Research on surface latent heat flux and land surface temperature anomalies in China and New Zealand reveals quasi-synchronous thermal disturbances occurring days to weeks before strong earthquakes. These studies demonstrate that thermal anomalies may reflect stress accumulation, gas emissions, or changes in subsurface fluid dynamics. However, most existing approaches apply statistical thresholds or moving averages, which often fail to capture abrupt, scale-dependent thermal variations, especially in regions with strong seasonal cycles [9], [10], [11].

To address these challenges, wavelet-based methods are gaining increasing popularity for analyzing non-stationary geophysical signals. In particular, the Continuous Wavelet Transform (CWT) offers superior capability to decompose signals into time–scale representations, enabling the detection of localized and transient anomalies. Previous works successfully apply wavelet transforms to ULF electromagnetic data and thermal infrared time series, demonstrating improved sensitivity to short-duration anomalies compared to Fourier-based techniques. Despite these advantages, many studies apply wavelets only as supplementary tools rather than as a central analytical framework [5], [18], [27].

Recent advances in remote sensing further expand the availability and resolution of thermal datasets, allowing for more systematic anomaly investigations. High-resolution satellite sensors and long-term datasets facilitate the exploration of thermal behavior across multiple temporal scales. Studies employing multi-year thermal records reveal recurring anomaly patterns associated with moderate to strong earthquakes. However, separating tectonic-driven anomalies from climatic influences remains difficult without explicit decomposition of trend, seasonal, and residual components, highlighting the need for integrated preprocessing and signal decomposition strategies [12], [15], [21].

Multi-parameter and multi-sensor approaches increasingly emerge as effective solutions to improve anomaly reliability. By combining thermal data with geomagnetic, ionospheric, or deformation measurements, researchers achieve more consistent interpretations of pre-seismic phenomena. Nevertheless, such fusion approaches introduce additional complexity and require careful synchronization of heterogeneous datasets. Wavelet-based analysis provides a unifying framework capable of handling these complexities by extracting scale-specific features across different data sources, making it particularly suitable for anomaly detection in geophysical time series [11], [23], [26].

Despite significant progress, a clear methodological gap remains in systematically applying the Continuous Wavelet Transform to long-term thermal anomaly analysis with explicit trend–seasonal separation. Many studies focus on isolated events or short time windows, limiting the generalizability of their findings. Therefore, exploring thermal anomalies using a structured CWT-based approach over extended temporal scales is essential to improve anomaly interpretability and robustness. This study addresses this gap by integrating temporal aggregation, decomposition, and wavelet analysis to provide deeper insights into thermal anomaly behavior and its potential geophysical significance [18], [19], [24].

2. Related Works

Early studies on geophysical anomalies emphasize the importance of detecting subtle temporal variations as indicators of tectonic activity. Zubaidah et al. investigate geomagnetic field anomalies in the Lombok Island region and demonstrate that local magnetic disturbances correlate with tectonic changes along complex subduction zones. Their work provides strong evidence that time-series geophysical signals contain precursor information; however, the analysis relies heavily on geomagnetic parameters and lacks integration with thermal or surface-based observations, limiting its applicability to multi-parameter anomaly detection frameworks [1], [2].

Research on ultra-low-frequency (ULF) electromagnetic signals further strengthens the role of time–frequency analysis in anomaly detection. Ida et al. and Adib et al. apply polarization analysis to ULF emissions and report statistically significant precursors before major earthquakes. These studies successfully capture transient anomalies that traditional Fourier-based methods fail to identify. Nevertheless, their reliance on electromagnetic data alone and sensitivity to noise underline the need for complementary approaches, such as thermal anomaly analysis, to improve robustness and cross-validation of precursory signals [3], [4].

Wavelet-based techniques gain increasing attention for analyzing non-stationary geophysical data. Febriani et al. apply wavelet transform and detrended fluctuation analysis to ULF signals in Java and show that wavelets effectively isolate anomaly-related frequency bands. This approach excels in handling multi-scale variations and short-lived disturbances. However, the study focuses primarily on electromagnetic data, leaving thermal signals—directly observable via satellite remote sensing—relatively underexplored despite their high spatial coverage and continuity [5].

Several studies establish a direct connection between seismic activity and thermal anomalies observed at the Earth's surface. Qin et al. identify surface latent heat flux anomalies preceding inland earthquakes in China and New Zealand, suggesting that thermal processes respond to stress accumulation in the crust. While these findings provide strong physical interpretations, the anomaly detection methods often depend on threshold-based or statistical deviation techniques, which struggle to separate seasonal patterns from true seismic-related signals [9]–[11].

Thermal infrared brightness temperature (TIR-BT) analysis has become a dominant approach in recent years due to advances in satellite sensing. Thee et al. and Rasul and Omar demonstrate that TIR anomalies emerge days to weeks before significant earthquakes and can be spatially associated with fault systems. Although these studies achieve promising results, many rely on fixed-window averaging or empirical anomaly indices, which may misclassify seasonal or climatic variations as seismic precursors without proper signal decomposition [12], [13].

More recent works attempt to improve anomaly reliability by combining multiple filtering and statistical techniques. Saradjian and Akhoondzadeh integrate interquartile analysis, wavelet transform, and Kalman filtering to detect thermal anomalies before earthquakes. This hybrid approach enhances noise suppression and anomaly clarity. However, the complexity of the framework and limited temporal resolution restrict its scalability for long-term monitoring and cross-dataset comparison [18].

Comprehensive reviews further reveal persistent challenges in earthquake precursor research. Conti et al. critically assess ground-based observations and conclude that inconsistency, lack of standardization, and poor separation between background variability and true anomalies remain major obstacles. Similarly, recent remote sensing reviews highlight the need for systematic, signal-based methods that can objectively decompose trends, seasonal components, and residual anomalies rather than relying on heuristic thresholds [20], [23].

Within this context, the Continuous Wavelet Transform emerges as a powerful and underutilized tool for thermal anomaly exploration. CWT enables simultaneous time–frequency localization, making it particularly suitable for isolating transient thermal signals embedded within long-term trends and seasonal cycles. While wavelet methods are widely applied in signal processing and biomedical domains, their systematic application to long-term thermal anomaly detection in geophysical studies remains limited. This gap motivates the present study, which leverages CWT to enhance anomaly interpretability, temporal precision, and robustness in thermal precursor analysis [27], [29].

3. Proposed Method

1. Dataset

In this study, we utilized thermal data obtained from NASA satellite observations and ground-based measurements from the LOK Geomagnetic Observatory to ensure comprehensive temporal and spatial coverage. The NASA dataset consists of hourly thermal data spanning the period from 2014 to 2018, downloaded through the NASA POWER Data Access Viewer from the website (<https://power.larc.nasa.gov/data-access-viewer/>), which provides standardized and long-term consistent satellite-derived temperature records. In parallel, we employed high-resolution temperature data from the LOK Geomagnetic Observatory, recorded at minute intervals, to capture detailed local thermal variations that cannot be fully resolved by satellite observations alone. The integration of these two datasets allows the analysis to benefit from the strengths of both sources: NASA satellite data offer stable, continuous, and large-scale temporal coverage, while the LOK observations provide fine-grained local sensitivity, enabling a more reliable investigation of thermal anomalies and their temporal dynamics.

2. CWT Method

The wavelet transform provides information that is localized in time and on a specific scale. This transform essentially decomposes a signal into a series of functions as a result of shifting and scaling the basis functions called *mother wavelet*. CWT is defined as [27]:

$$CWT(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t) \psi^* \left(\frac{t-b}{a} \right) dt \quad (1)$$

The resulting transformed signal is a function of two variables, namely a (dilation) and b (translation). $f(t)$ is a signal that is analyzed and $\psi(t)$ is the wavelet analyzer. $\frac{1}{\sqrt{|a|}}$ is the energy normalization so that the transformed signal will have the same energy at every scale. The wavelet for thermal analysis proposed in this study is a complex Gaussian Wavelet which has local representation properties that allow the separation and detailed analysis of certain parts of the data that have different frequency characteristics. This local representation allows for more detailed analysis and the discovery of finer patterns in the data [27]. A complex Gaussian wavelet of order p is defined as the p th derivative of the complex Gaussian wavelet function:

$$\psi(t) = d^p (C_p \text{and}^{-it} * \text{and}^{-t^2}) / dt \quad (2)$$

Where C_p is a constant, $\psi(t)$ complex Gaussian wavelet function, t is time. The calculation of the CWT transform involves the convolution of the signal with the mother

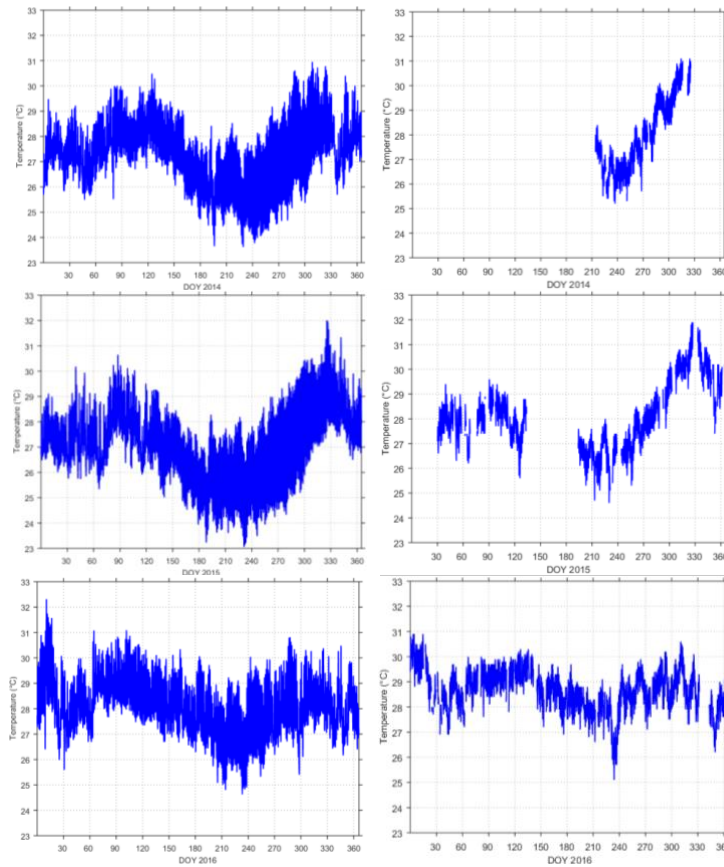
wavelet at different scaling factors. The wavelet coefficients $CWT(a,b)$ are matrix coefficients that indicate the similarity of the analyzed signal with the mother wavelet [28].

Table 1. Mw>6 earthquake events in 2018 on Lombok Island

No.	Date/Time (UTC)	Location	Depth (km)	Magnitude
1	2018 – 07 – 28/22:47:38	8.230°S 116.508°E	14	6.4
2	2018 – 08 – 05/11:46:38	8.258°S 116.438°E	34	6.9
3	2018 – 08 – 19/04:10:22	8.337°S 116.599°E	16	6.3
4	2018 – 08 – 19/14:56:27	8.319°S 116.627°E	21	6.9



Fig. 1. Location of the Mw>6 earthquake on Lombok Island in 2018



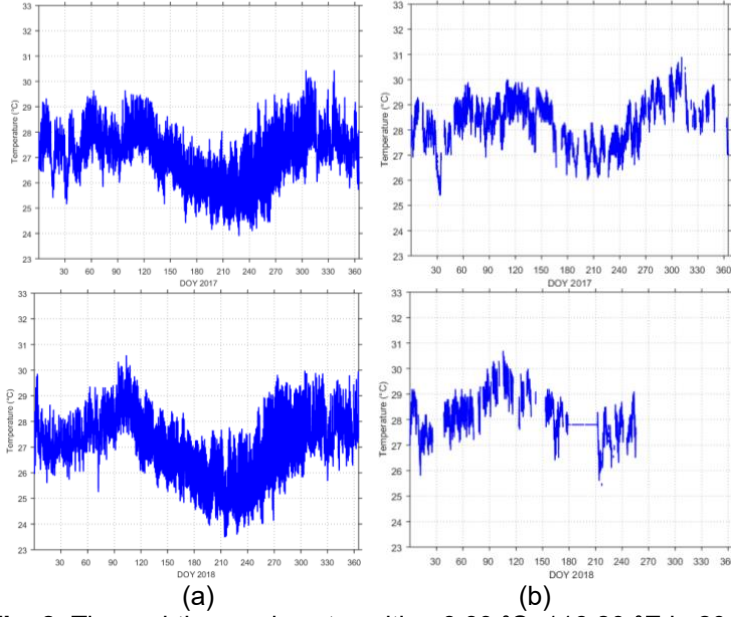


Fig. 2. Thermal time series at position 8.83 °S, 116.29 °E in 2014-2018
(a) NASA satellite source (b) LOK Geomagnetic Observatory source

In this study, we conducted thermal data processing using The study acquires temperature data from NASA and LOK covering the period 2014–2018 and performs monthly temporal aggregation. For each year and each month $b \in \{1, \dots, 12\}$, all available daily average temperatures are collected and averaged to obtain a monthly mean, as defined by $\bar{T}_{b,y} = \frac{1}{n_{b,y}} \sum_{d \in b} T_{d,y}$, where $n_{b,y}$ denotes the number of valid daily records in month b of year y . If no valid data exist for a given month, the monthly value is set to NaN. This process yields a 12×1 vector for each year, which is subsequently concatenated into a continuous 60-month time series spanning January 2014 to December 2018 for each data source.

The consolidated time series is decomposed into trend, seasonal, and residual components. The trend component T_t is estimated using a 12-month centered moving average, while the seasonal component S_t is derived by averaging corresponding months across years and centering the seasonal indices such that $\sum S_b = 0$. The residual component is then calculated as $R_t = \bar{T}_t - (T_t + S_t)$, where \bar{T}_t represents the observed temperature. To support continuous wavelet transform (CWT) analysis, lightweight interpolation using Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) is applied to the seasonal and residual components. The CWT with the cgau4 wavelet is then performed on both components, enabling visualization and interpretation of seasonal and residual patterns over the 60 months, as well as the identification and comparison of anomalous temperature hot-spots between the NASA and LOK datasets.

5. Result and Analysis

5.1 Characteristics of CWT Results

Analysis *Continuous Wavelet Transform* (CWT) is applied to the observed thermal data (y), which represents the monthly average temperature from two sources, namely NASA satellite observations and surface observations at the LOK Observatory. Component

thermal residue calculated through additive decomposition $R = y - (T + S)$, with y represents temperature monthly observations, T is long-term trends, and S is periodic seasonal components. The R component or residual represents non-periodic fluctuations that potentially reflect transient processes due to the interaction of the atmosphere–lithosphere system. Data y then decomposed additively into three main components, is the long-term trend (T), periodic seasonal component (S), and residual $R = y - (T + S)$. This residual component is used to detect non-stationary thermal anomalies, because it describes non-periodic fluctuations that can be related to changes in the energy of the atmosphere–lithosphere system before a seismic event.

The CWT transform using a fourth-order complex Gaussian wavelet (cgau4) produces a two-dimensional power spectrum map representing the energy distribution over time and period scales. In the visualization, blue indicates low (stable) energy, yellow indicates moderate energy increases, and deep red represents the highest thermal energy or the strongest fluctuating activity. The analysis results indicate the presence of high-energy anomalies that appeared before the 2018 Lombok earthquake, especially in surface observation (LOK) data.

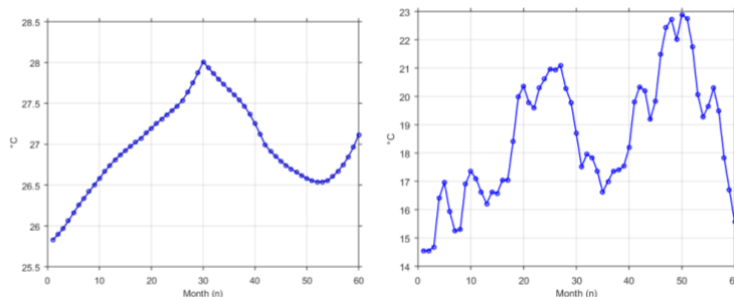


Fig. 3. Thermal trends at position 8.83 °S, 116.29 °E in 2014-2018
(a) NASA Satellite (b) Geomagnetic Observatory LOK

5.2 Quantitative Results of CWT

a. NASA Satellite Thermal Data (2014-2018)

The CWT image results against NASA temperature data residuals show that the highest energy anomaly occurred in 2016. The yellow to orange color pattern appeared starting in April and reached a deep red peak in October 2016, with a maximum energy value recorded of 16.42 (relative scale) on a period scale of about 11–12. After 2016, energy intensity decreased significantly and remained stable until 2018, indicating no new anomalies leading up to the Lombok earthquake. In general, the 2016 energy peak reflects a large-scale regional thermal anomaly, likely influenced by the 2015–2016 El Niño phenomenon. This phenomenon increased sea surface temperatures in central Indonesia and decreased atmospheric humidity, leading to higher land surface temperatures. Therefore, the 2016 NASA CWT energy increase is climatological in nature, rather than pre-seismic geophysical.

b. LOK Observation Thermal Data (2014-2018)

In contrast to NASA's findings, surface observation data at LOK showed a very strong energy anomaly in 2018. The yellow color pattern began to appear in January 2018, indicating an initial energy increase, then developed into a deep red in May–June 2018, with a maximum energy value recorded at 2974 (relative magnitude) at a period of 11.5. After reaching the highest energy peak, the spectrum showed a gradual decrease until

October 2018.

The presence of a deep red color between May and June 2018 is interpreted as the strongest thermal anomaly during the observation period, which occurred approximately two months before the major Lombok earthquake (July 29, 2018). The duration of this energy increase, which began in January and peaked in June, indicates that the thermal anomaly had been developing for approximately six months before the seismic event, reflecting potential pre-earthquake thermal precursors relevant to increased subsurface tectonic activity.

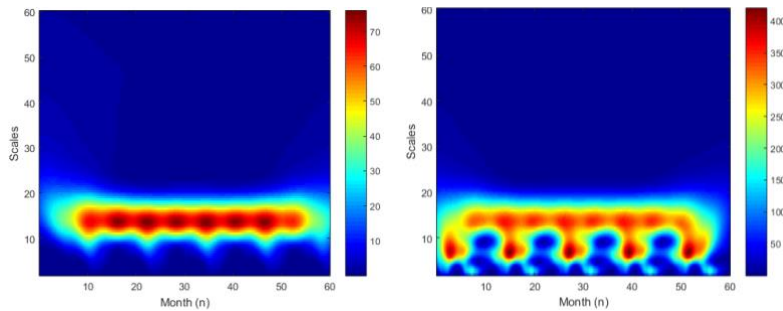


Fig. 4. Seasonal Temperature at position 8.83 °S, 116.29 °E in 2014-2018
(a) NASA Satellite (b) Geomagnetic Observatory LOK

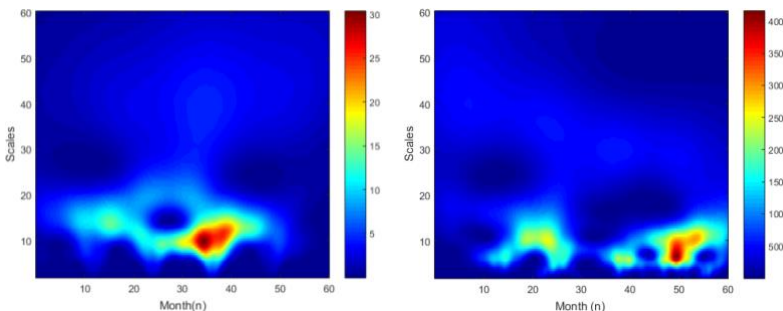


Fig. 5. Temperature residue at position 8.83 °S, 116.29 °E in 2014-2018
(a) NASA Satellite (b) Geomagnetic Observatory LOK

5.3 Thermal Anomaly Dynamics

a. Based on NASA Data (2014–2018)

The increase in energy in NASA's 2016 thermal residual was likely influenced by the global climate phenomenon El Niño, which increased direct solar radiation and reduced rainfall. During this period, the land surface temperature in the Nusa Tenggara region increased due to reduced humidity and increased evaporation. This anomaly indicates large-scale (regional) atmospheric warming that is not directly related to seismic activity, but can be considered as a thermal precondition that strengthens the sensitivity of the atmosphere and the Earth's surface to tectonic stress in subsequent years. After 2016, the CWT energy decreased, indicating that atmospheric conditions stabilized again until 2018.

b. Based on LOK Data (2014–2018)

The CWT results on the thermal residuals of LOK observations show a strong and sustained energy anomaly starting in January 2018, with the intensity increasing to a deep

red peak in May–June 2018, then decreasing towards October 2018. The January–May period in Lombok is a transition from the rainy season to the dry season. Climatologically, this causes an increase in temperature due to decreased humidity and increased solar radiation. However, the very high CWT energy intensity (deep red color) far exceeds normal seasonal variations, so it cannot be explained solely by meteorological factors.

This energy increase likely reflects subsurface geophysical activity that began to increase several months before the major earthquake. The most likely mechanisms include increased tectonic stress in the shallow crust, migration of hydrothermal fluids that amplified local thermal gradients, and the emergence of microfractures that released latent heat into the surface atmosphere. After peak energy was reached in May–June 2018, a gradual decline through October indicates the release of elastic energy and heat redistribution resulting from the series of Lombok earthquakes in July–August 2018. Thus, the LOK observation results indicate that pre-earthquake thermal anomalies occurred about six months before the seismic event, which is consistent with reports of thermal precursors in other active seismic zones such as [29] and [13].

6. Conclusion

This study demonstrates that the CWT is an effective approach for identifying non-stationary thermal anomalies when applied to decomposed temperature residuals derived from long-term satellite and ground-based observations. By separating the observed temperature signals into trend, seasonal, and residual components, the analysis isolates irregular thermal fluctuations that are more likely associated with transient geophysical processes rather than climatic seasonality. The CWT power spectrum successfully reveals time–frequency characteristics of thermal energy variations, allowing clear visualization of anomaly intensity, duration, and temporal evolution from 2014 to 2018.

The comparative results between NASA satellite data and LOK surface observations highlight the importance of data source resolution and locality in thermal anomaly detection. NASA data show a significant energy peak in 2016, which the analysis attributes to large-scale climatological forcing, particularly the 2015–2016 El Niño event, rather than seismic processes. In contrast, LOK observations exhibit a pronounced and sustained high-energy anomaly beginning in early 2018 and peaking in May–June 2018, approximately two months before the major Lombok earthquake. The magnitude, persistence, and timing of this anomaly exceed normal seasonal variability, strongly suggesting a link to pre-seismic processes occurring in the shallow crust.

The findings indicate that locally observed thermal residuals, when analyzed using CWT, provide stronger and more reliable signals of potential pre-earthquake thermal precursors than satellite-based data alone. The results support the hypothesis that increased tectonic stress, fluid migration, and microfracturing can manifest as measurable surface thermal anomalies several months before a major seismic event. Future work should focus on integrating multi-parameter datasets, such as geomagnetic, ionospheric, and gas emission observations, with CWT-based thermal analysis to improve precursor reliability, reduce false positives from climatic effects, and advance the development of robust, operational earthquake monitoring frameworks.

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