

# Statistical analysis of the two-decade ASTER archive: Quantitative retrievals of volcanic thermal and gas emissions

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## Abstract

Detailed analysis of volcanic thermal and gas emissions over time can constrain subsurface processes throughout the pre- and post-eruption phases. Time series analyses are commonly applied to high temporal datasets like the Moderate Resolution Imaging Spectroradiometer (MODIS); however, this is the first study using the entire Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) twenty-plus year archive. The ASTER archive presents a unique opportunity to quantify volcanic precursors and processes. The spatial, spectral, and radiometric resolution of its thermal infrared (TIR) subsystem allows detection of very low-magnitude surface temperature anomalies and passively emitted small gas plumes. We developed a new statistical algorithm to automatically detect these subtle anomalies and applied it to five recently active volcanoes with well-documented eruptions: Taal (Philippines), Popocatepetl (Mexico), Mt. Etna (Italy), Fuego (Guatemala), and Kluichevskoi (Russia). More than 3,300 ASTER level-1 terrain corrected (L1T), registered, radiance-at-sensor images were downloaded from the NASA EARTHDATA website. These were screened for significant summit cloud coverage, which removed approximately 25% of scenes. The remaining were converted to brightness temperature and a median background temperature per scene was determined from an annulus around the active crater to produce the temperature above background. The algorithm creates a rejection criterion value defined by the median absolute deviation to identify the thermal anomalies. The size and intensity of these anomalies as well as the detection, composition, emission rate of small plumes are retrieved one year prior to the known eruptions for each volcano to identify all precursory signals. The results of this study have the dual purpose of constraining volcanological processes that lead to eruptions as well as providing training data for machine learning modeling. Machine learning is an effective and well-established technique that provides rapid classification of volcanic activity such as thermal anomalies that exceed a certain size and/or intensity. The comparison of these two approaches is documented in a companion abstract in this session.

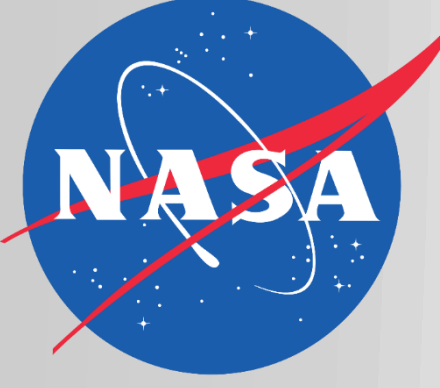




# Statistical analysis of the two-decade ASTER archive: Quantitative retrievals of volcanic thermal and gas emissions (V35E-0178)

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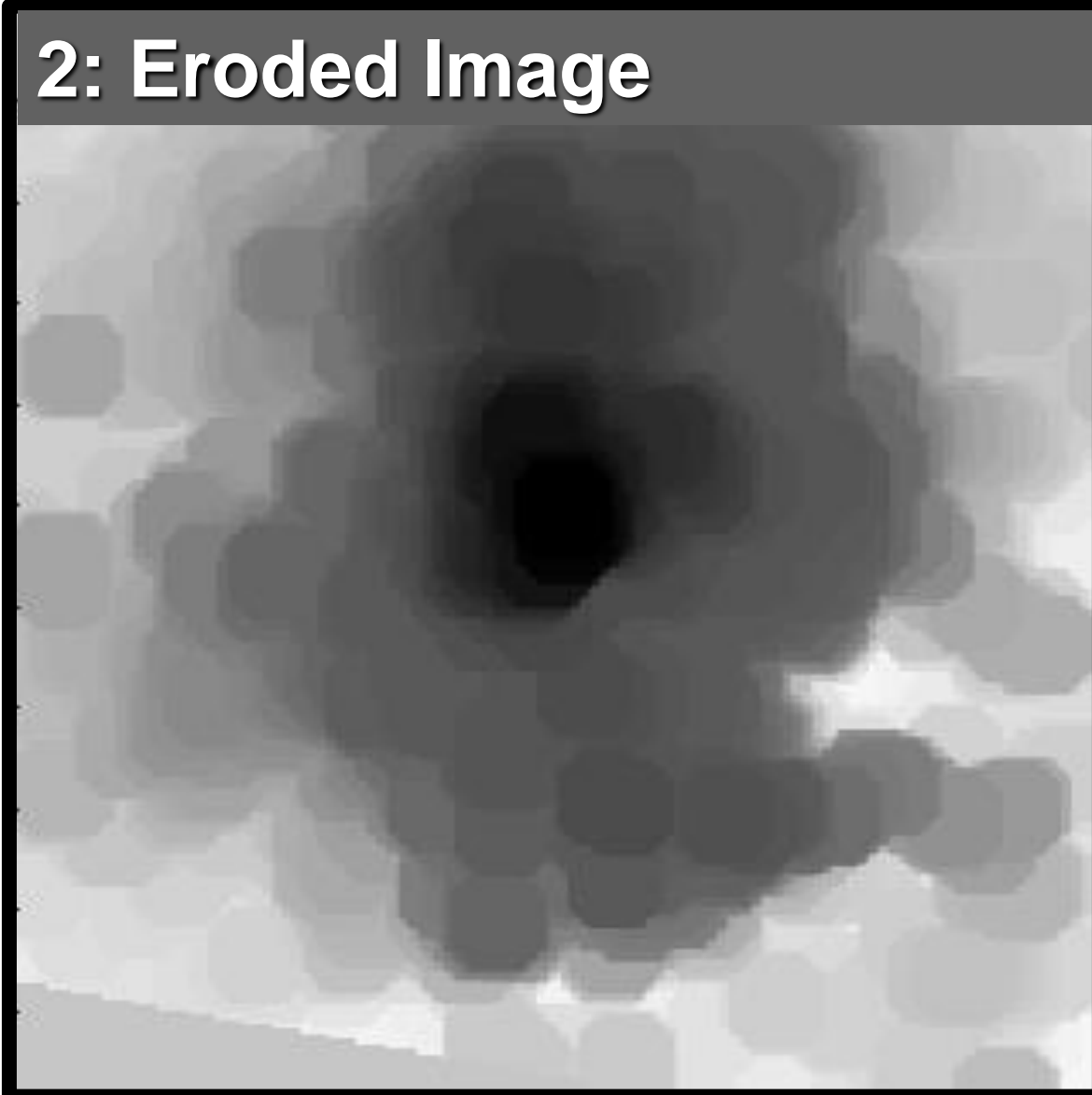
## Automatic Thermal Anomaly Retrieval Process

### 1: Original Image



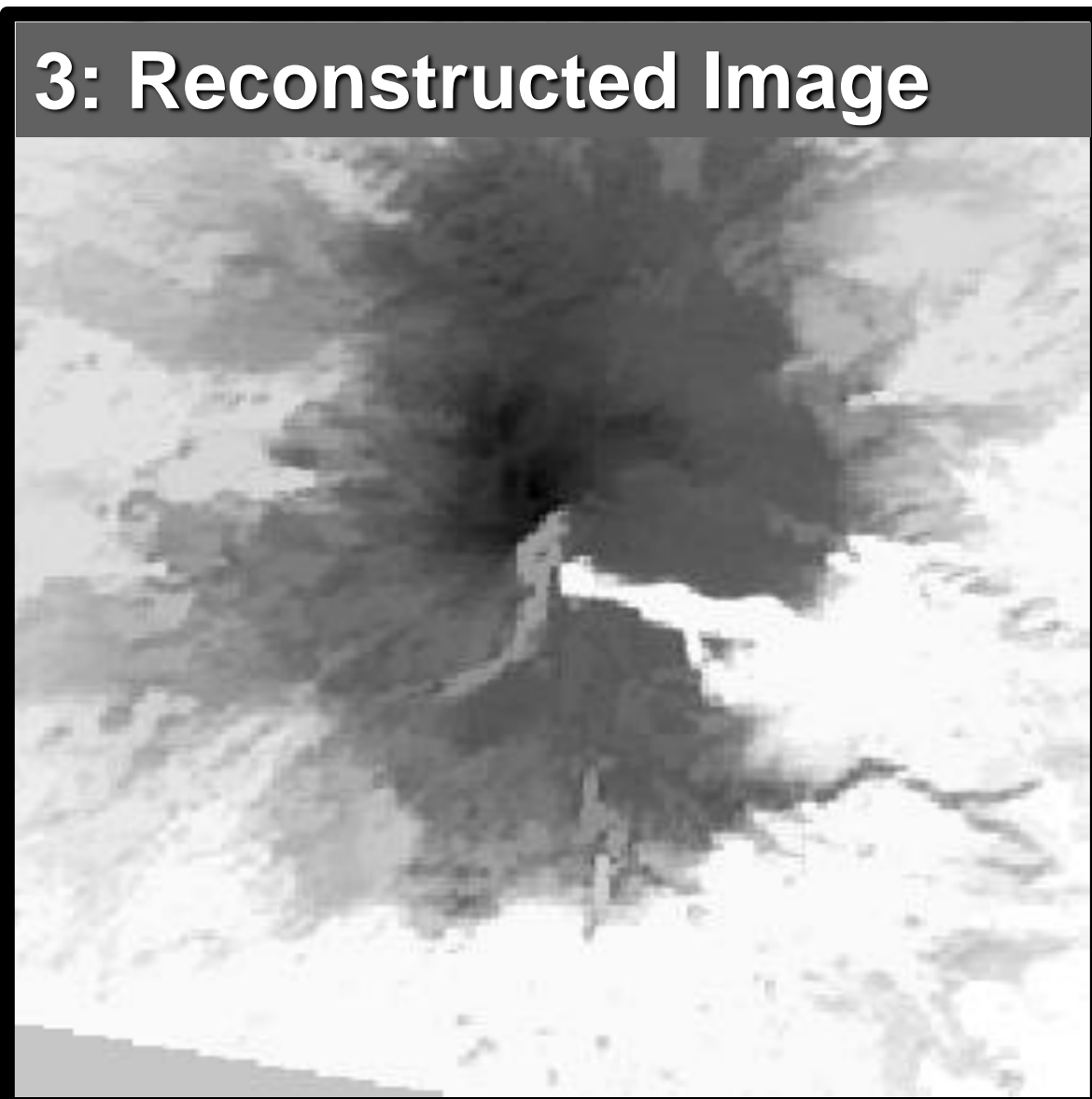
ASTER L1T data are retrieved from the Earthdata archive and converted to brightness temperature (BT).

### 2: Eroded Image



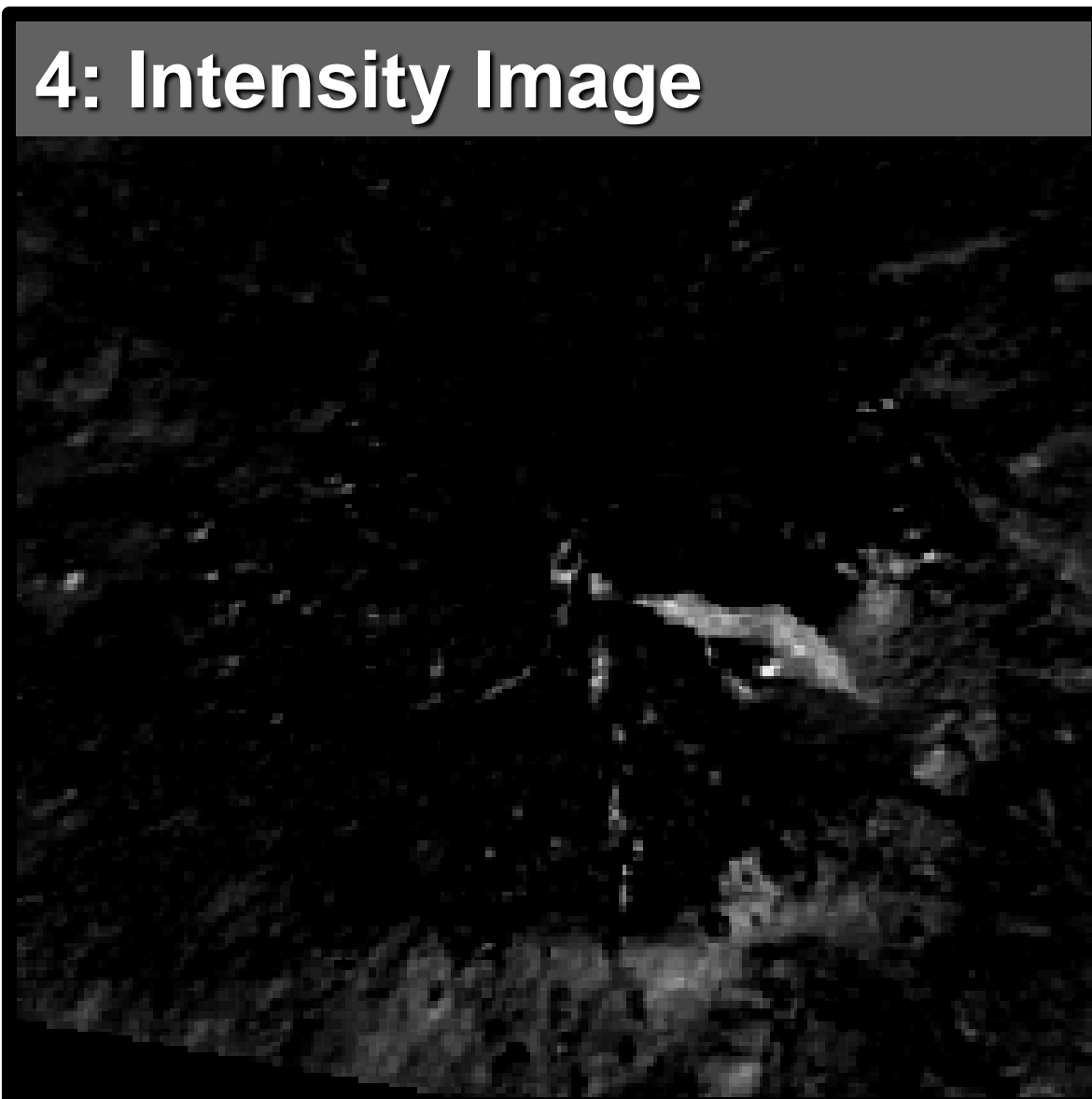
The **Original Image** is then eroded with a 10 – pixel disk to create a regional background image.

### 3: Reconstructed Image



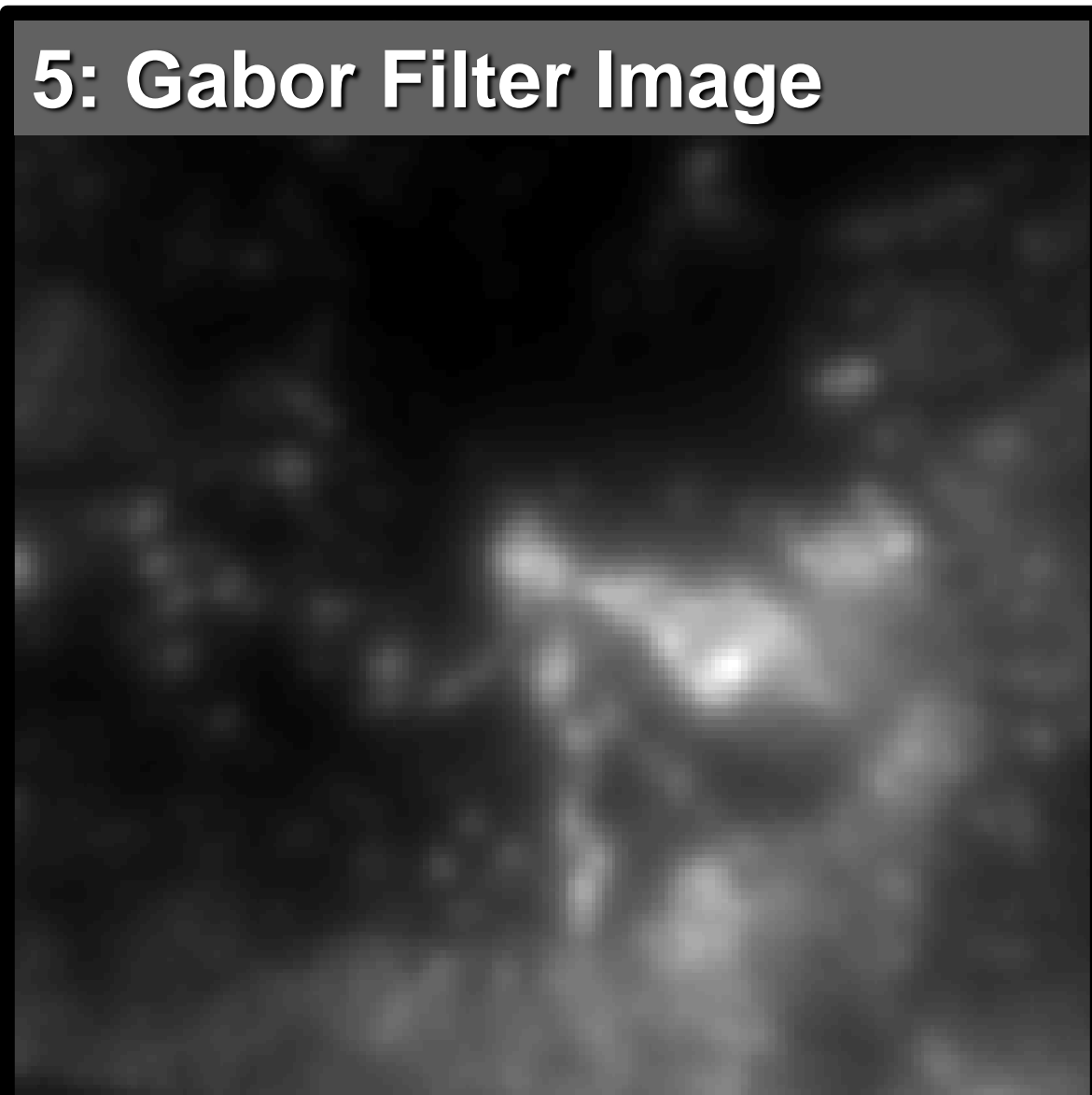
A new image is reconstructed from the **Original Image & Eroded Image** to dilate the intensity peaks.

### 4: Intensity Image



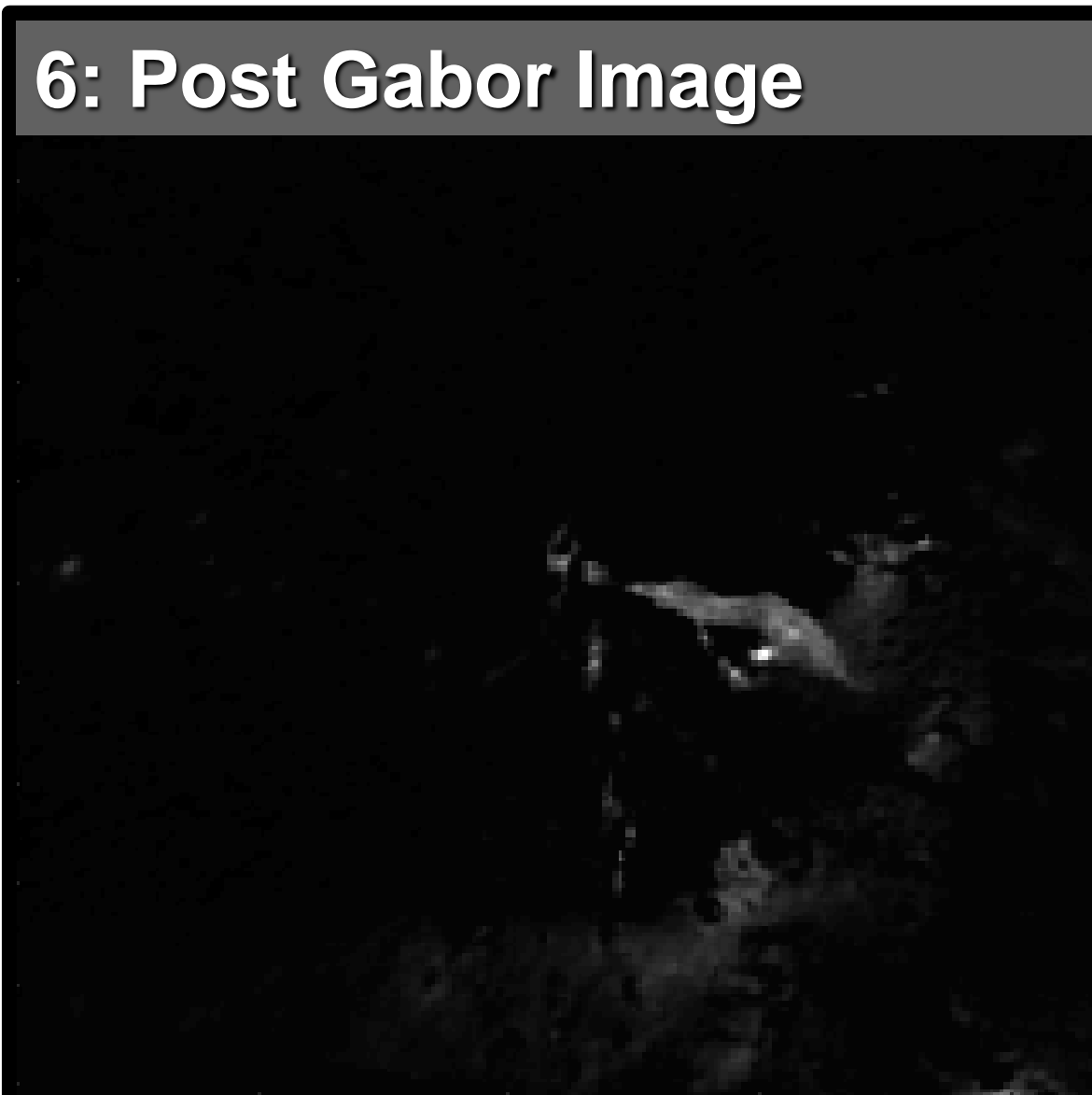
The **Reconstructed Image** is subtracted from the **Original Image** to highlight any 'anomalous' pixels.

### 5: Gabor Filter Image



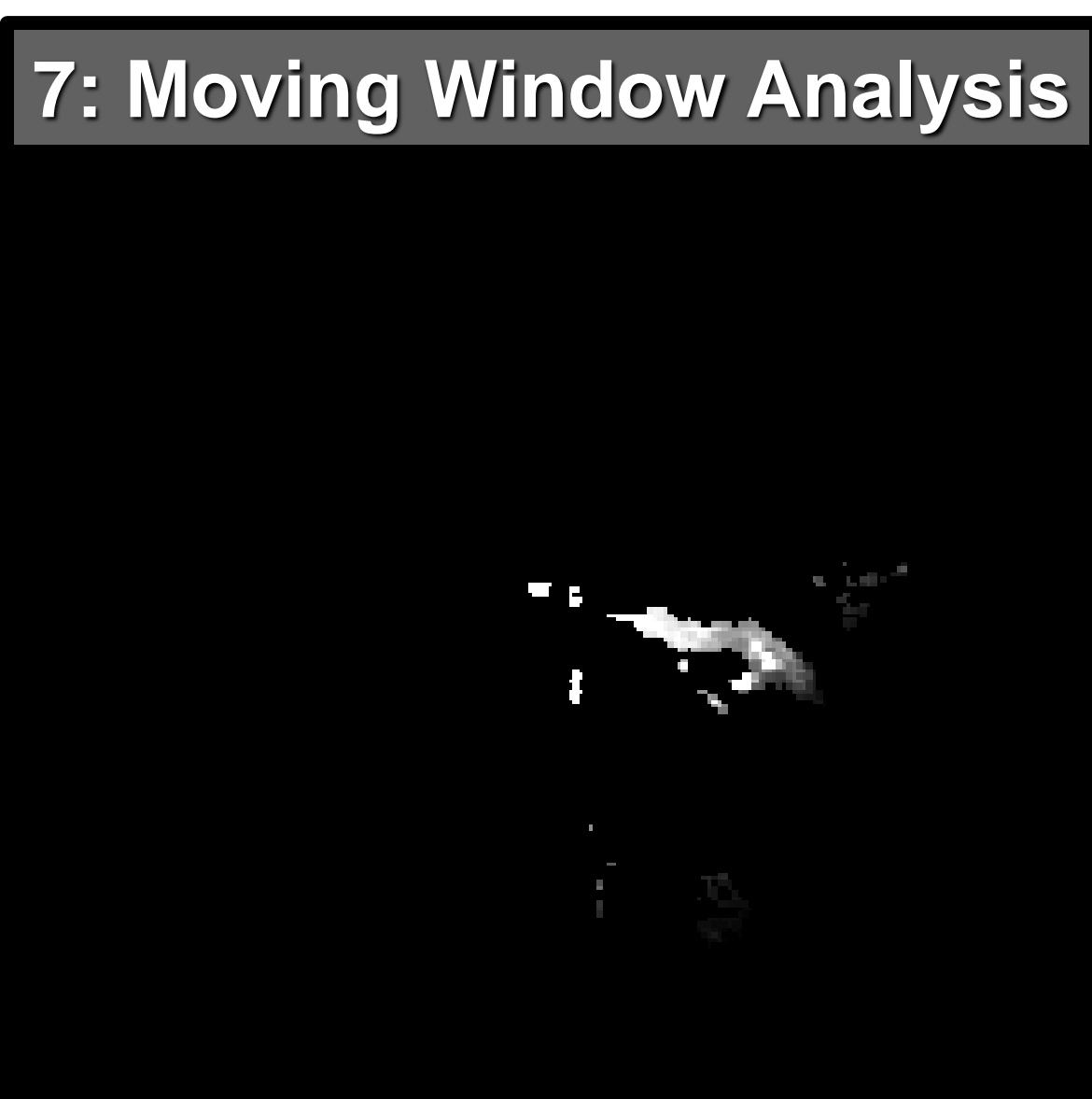
A **Gabor Filter** is applied to highlight spatial edges and anomalous pixels.

### 6: Post Gabor Image



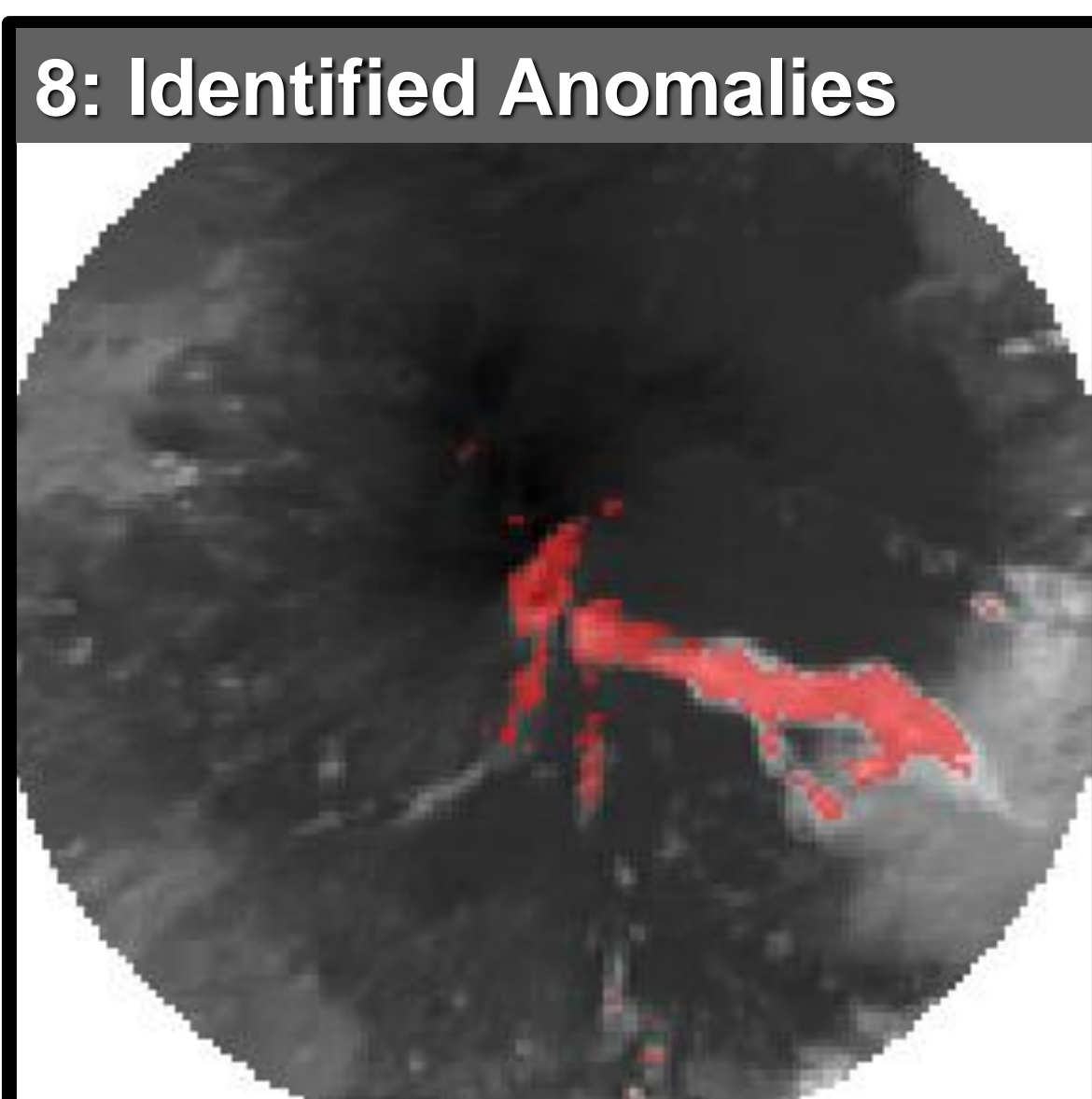
The **Intensity Image** is multiplied by the **Gabor Filter Image** to weight each pixel based on intensity and spatial features.

### 7: Moving Window Analysis



A filter is applied to the **Post-Gabor Image** and if pixel > (75<sup>th</sup> percentile + (1.5\*IQR)) is flagged as anomalous.

### 8: Identified Anomalies



The local minimum after the main local max in the **Moving Window** histogram is set as the threshold value.

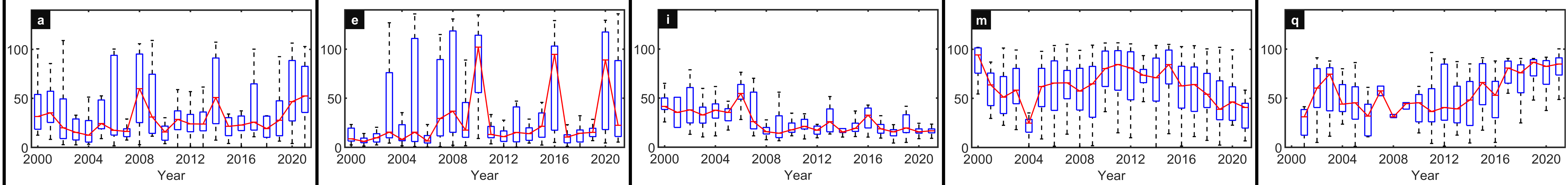
## Introduction

Detailed analysis of volcanic thermal emissions over time can constrain subsurface processes throughout the pre- and post-eruption phases. Time series analyses are commonly applied to high temporal datasets like the Moderate Resolution Imaging Spectroradiometer (MODIS); however, this is the first study using the entire Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) twenty-plus year archive. The ASTER archive presents a unique opportunity to quantify volcanic precursors and processes. The spatial, spectral, and radiometric resolution of its thermal infrared (TIR) subsystem allows detection of low-magnitude subtle surface temperature anomalies (~0°C). This study has the dual purpose of constraining volcanological processes that lead to eruptions as well as providing training data for machine learning (ML) modeling. Machine learning is an effective and well-established technique that provides rapid classification of volcanic activity such as thermal anomalies that exceed a certain size and/or intensity. The comparison of these two approaches is documented in a companion abstract and poster (V35E-0176) in this session.

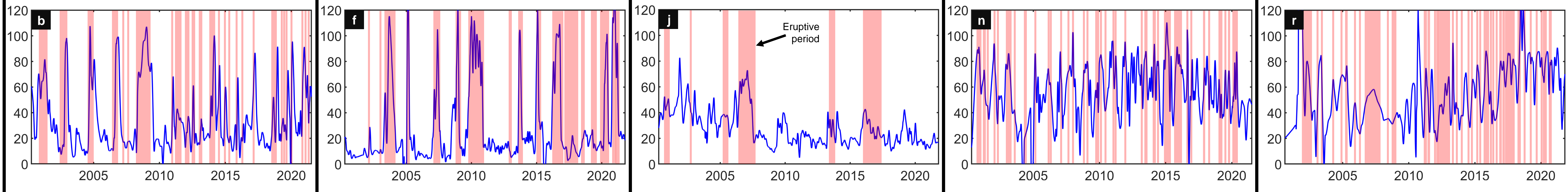
## Target Volcanoes



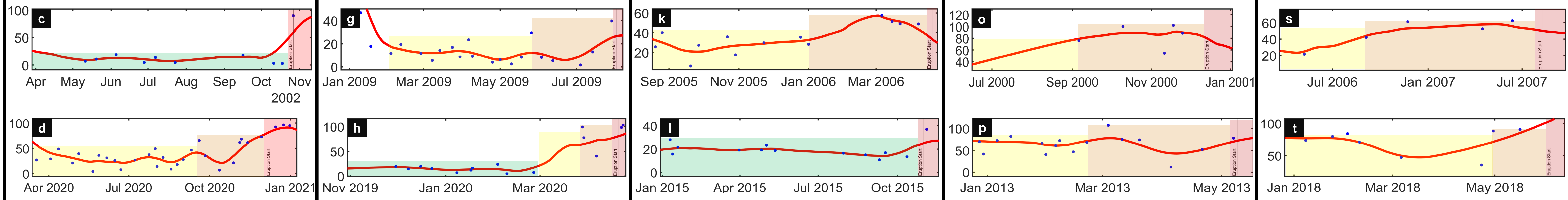
Boxplots of maximum anomaly temperature above background (TAB) for each year (°C). Red line shows the yearly trend.



Monthly moving average plot of maximum anomaly TAB (°C). Red areas represent documented eruptive periods (Global Volcanism Program, Smithsonian Institution).



ASTER precursor activity with color coded levels: green (normal), yellow (unrest), orange (heightened unrest), red (eruption) (Reath et al. 2016). Maximum anomaly TAB (°C).



## Summary

In this study we created a new method process to identify subtle thermal changes over targeted volcanoes for the entire ASTER 21-year archive. Increases in thermal activity match most documented eruptive periods for each volcano throughout the time series. Precursory activity is normally detected months before an eruption. For example, the Etna Dec. 9, 2020, eruption had normal levels of unrest from April – September, followed by a heightened period of unrest leading to the eruption Sep – Dec (Fig. d). However, there are some eruptions that do not show precursory signals. For example, the Etna Oct. 26, 2002, and the Lascar Oct. 30, 2015, eruptions had normal background activity followed by an abrupt eruption (Fig. c,l). This may be caused by either a gap in data where the increase in activity was not observed, or a real volcanological process where precursory activity was not present. Two weeks before the Oct. 26, 2002, Etna eruption, degassing and ash emission were documented with no thermal emission (Global Volcanism Program, Smithsonian Institution). The results of this study have the dual purpose of detecting volcanological processes that lead to eruptions as well as providing training data to train an AI to automatically detect these thermal anomalies, for more details on this work see poster V35E-0176.

## Acknowledgements

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