Annotated Coadds: Concise Metrics for Characterizing Survey Cadence and for Discovering Variable and Transient Sources

David L. Shupe , Frank J. Masci , Ranga Ram Chary et.al

reporter：xiao chunsheng
2025.11.07

1.Introduction

2.Characterization of Survey Cadence

3.Pixel-based Variability Metrics

4.Summary

Introduction

Time-domain phenomena (variable and transient sources),such as stellar flares, pulsating variable stars, novae, and supernovae,are important subjects of astrophysical research.

With the launch of various large-scale survey projects, an enormous amount of astronomical observational data is being produced.This paper proposes a framework, Annotated Coadds, to address the problem of efficiently identifying variable and transient phenomena from massive datasets.

Currently, the commonly used methods for identifying variable and transient sources can be roughly divided into two categories: difference imaging and light curve analysis, which operate respectively at the image level and the data level.

The Annotated Coadds framework offers a new approach , combined image and data analysis , by quantifying the historical observations at a given sky position (or pixel) to determine whether a variable source exists at that location.

The Annotated Coadds method consists of two main steps: Characterization of Survey Cadence and Pixel-based Variability Metrics.

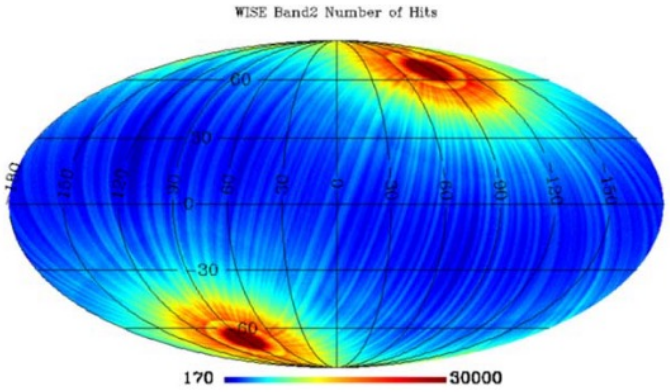
Characterization of Survey Cadence

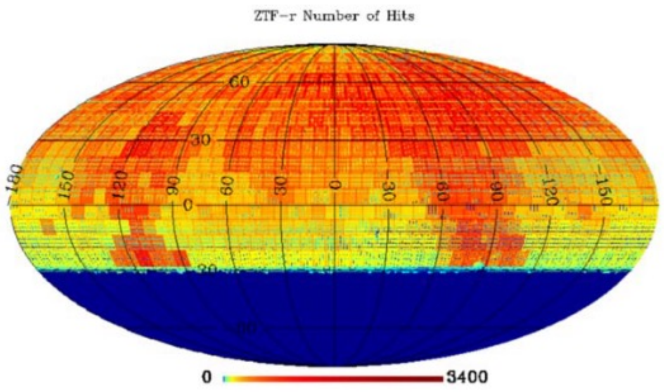
1. Use HEALPix to divide the sky into equal-area, equal-dimension grids.

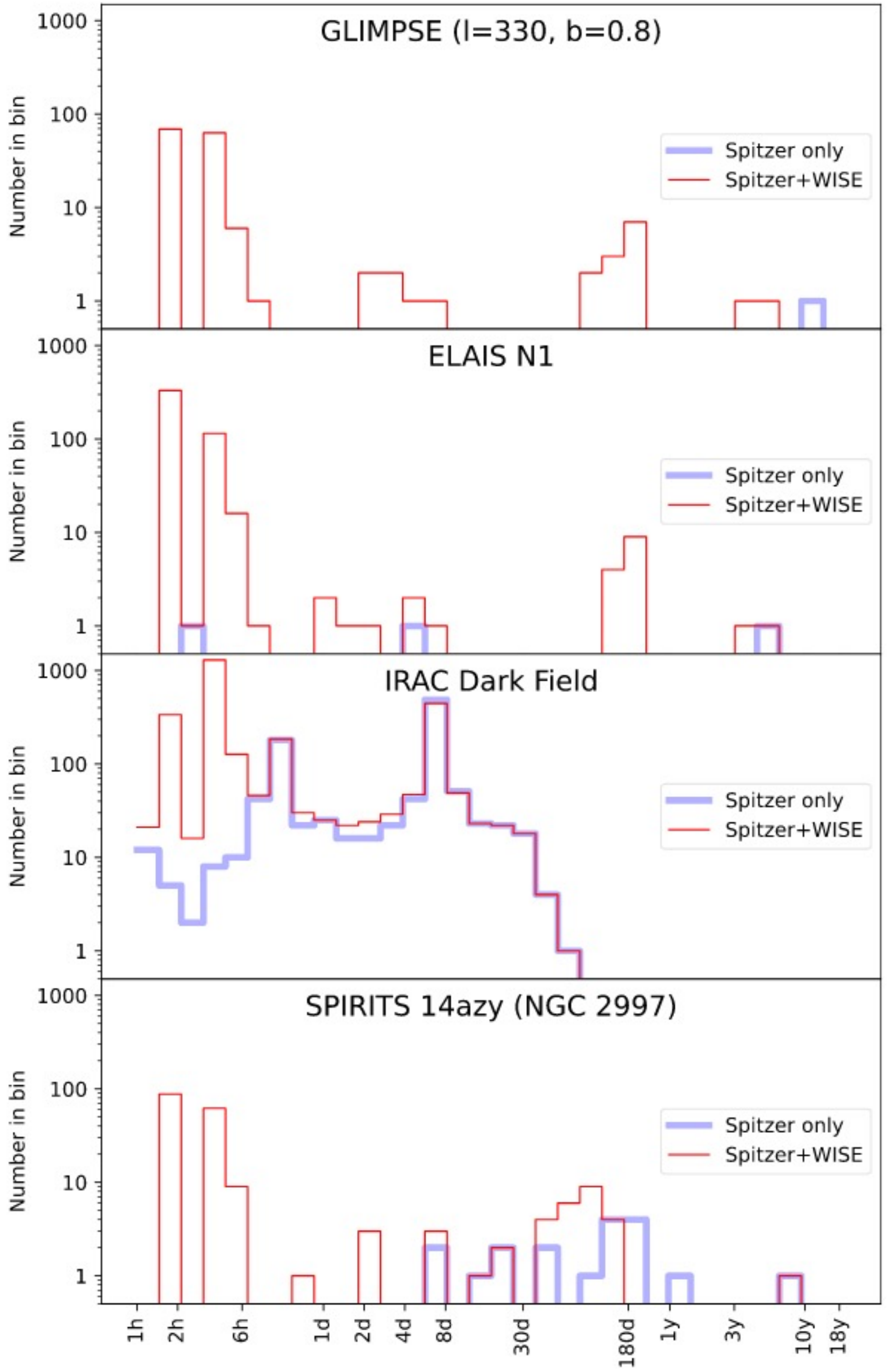
2. Project each observational image onto the corresponding HEALPix pixels, recording the observation time and depth for each exposure.

3. Examine the number of observations, time coverage, and cadence for each pixel.

4. Select appropriate regions for variable source searching.

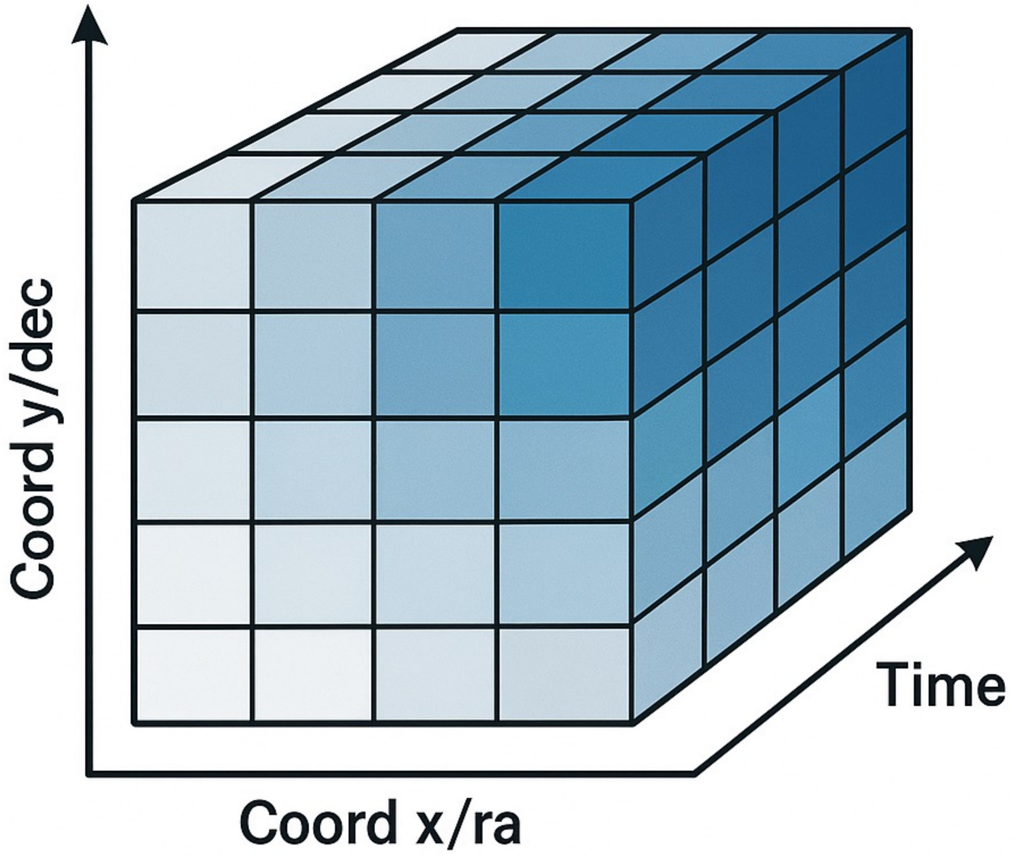






Pixel-based Variability Metrics

1. Use SWarp to align historical observational images of a given sky position and re-grid them onto a common grid.
   i. Positional alignment
   ii. Relative flux normalization
2. Stack all aligned images together to create a data cube.
3. Analyze whether the flux at a given pixel position (or ra/dec) varies over time.



Pixel-based Variability Metrics

1.Reduced Chi-squared

Principle: assuming that the brightness at each pixel remains constant, calculate how much the real data deviate from the model relative to the noise level.

chi-squared was computed as:

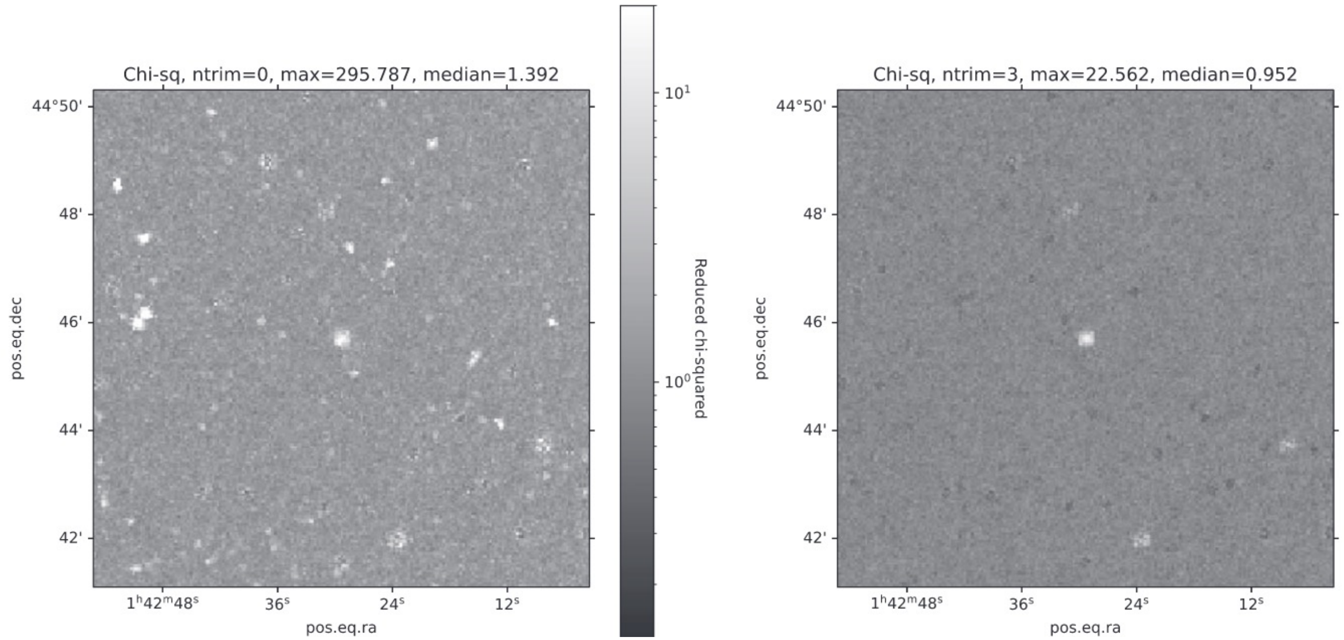
$$\chi_i^2 = \frac{1}{\sigma_i^2} \sum_t (p_{it} - I_{\mathrm{median},i})^2 \qquad (2)$$

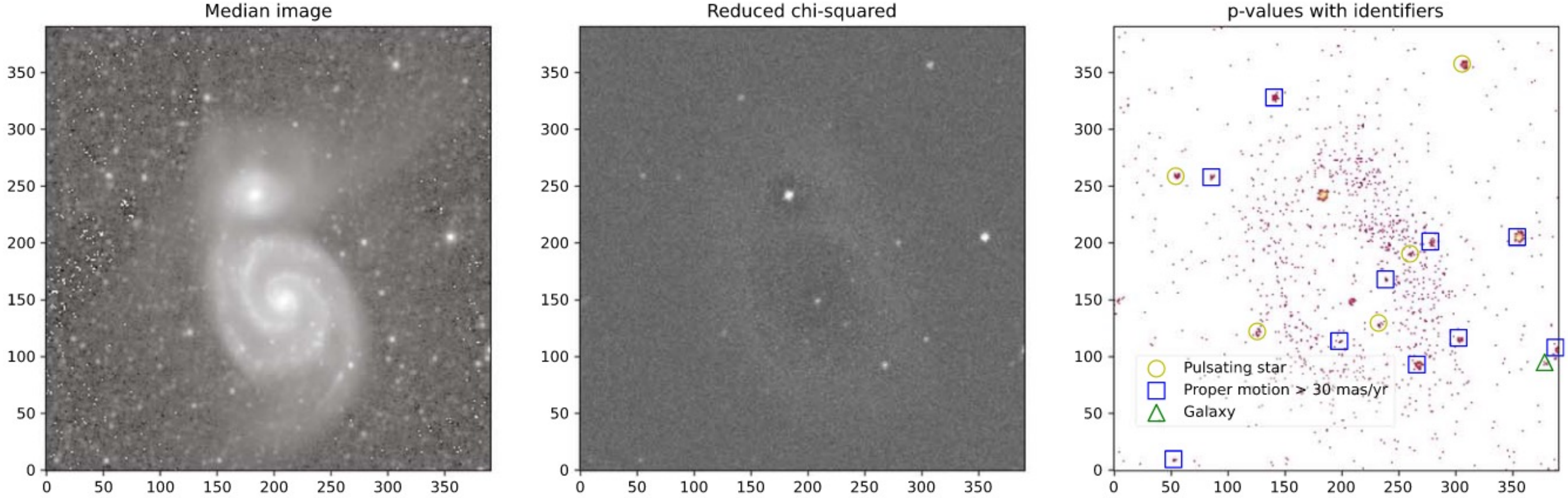
over all valid data values in the "temporal stack" ($t = 1...N$) for each sky pixel i. The reduced chi-squared is then:

$$\chi_{\mathrm{red},i}^2 = \frac{\chi_i^2}{(N-1)} \qquad (3)$$

For variable sources, the Reduced Chi-squared values in their covered pixel regions should be significantly greater than 1. We create a Reduced Chi-squared map that represents the magnitude of the Reduced Chi-squared for each pixel using color.

The pixel-based Reduced Chi-squared not only enables the identification of variable sources but can also reveal high proper motion stars.





Pixel-based Variability Metrics

2.Consecutive Signed-difference Run Length (CSDRL)

Principle: the brightness of a variable source changes continuously over a period of time. By subtracting temporally adjacent data and examining the duration of consecutive changes in the same direction, we can quantify the significance of a source's variability.

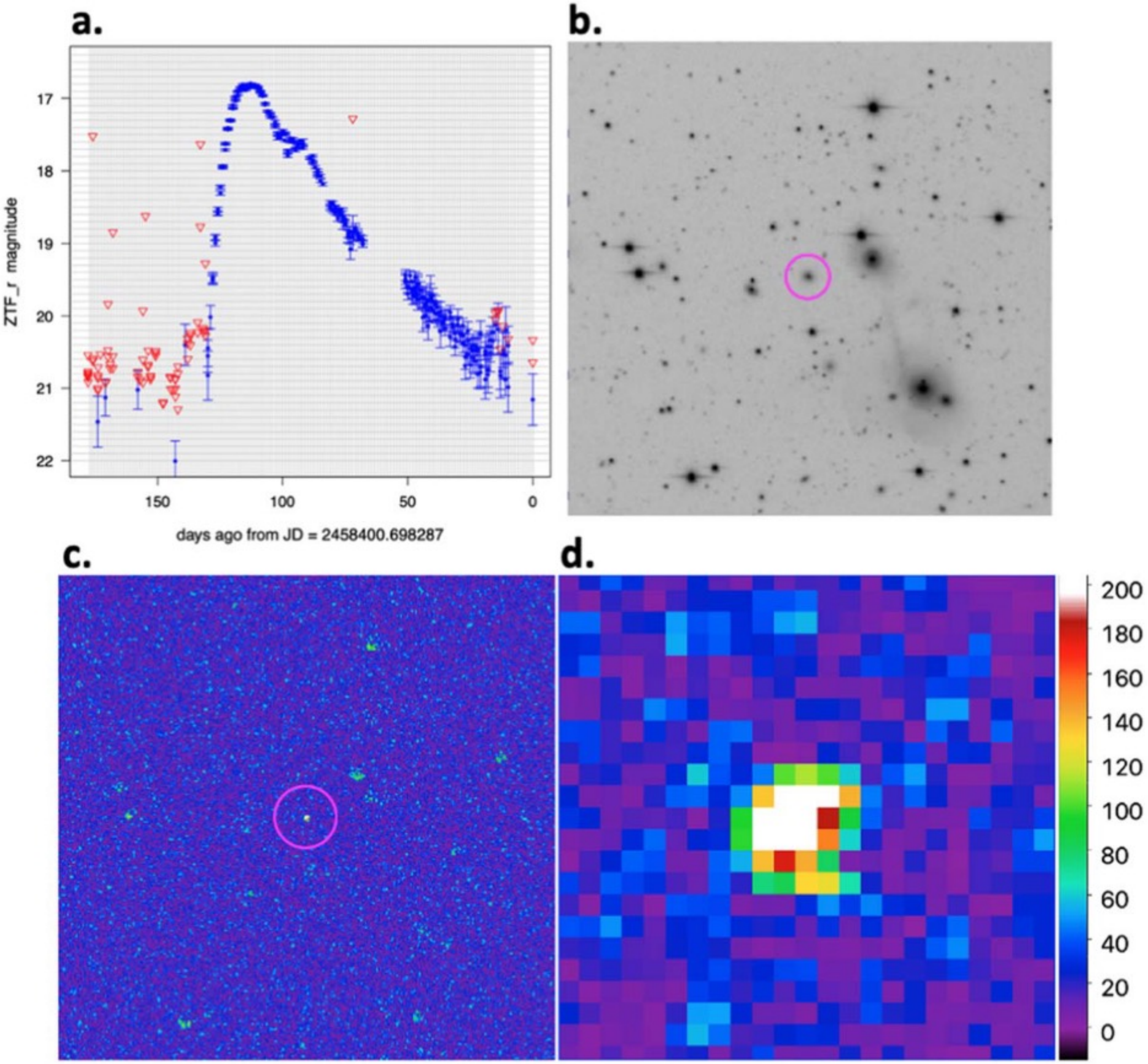
(1)Sort all images by time to create a data cube at the pixel level.

(2)Apply median filtering to the time series of each pixel to suppress noise between consecutive data points.

(3) Compute the first-order differences for each pixel's time series, $D_t = f_{t+1} - f_t$.

(4) Identify the longest consecutive run of positive or negative differences and assign it to the corresponding pixel.

(5)Take the absolute value of the run lengths for all pixels to generate the CSDRL map.



(a) Lightcurve of Type-Ia supernova 2018cfa discovered in the ZTF r-filter in 2018 June.

(b) Median image that collapses 335 ZTF r-filter exposures centered on the location of the SN. Image measures ∼8.1 × 8.1 arcmin^2.

(c) Image of the CSDRL metric from collapsing all 335 exposures with the SN clearly detected.

(d) Zoom-in on SN 2018cfa on the CSDRL metric image measuring ∼23 × 23 arcsec^2. The color-bar represents the range in CSDRL pixel values.

Pixel-based Variability Metrics

3.Tensor Decomposition

Principle: Using Tensor Robust PCA (TRPCA), a time-series image dataset (i.e., a tensor) is automatically decomposed into two main components: a low-rank part representing the static, stable background, and a sparse part representing transient or outlier signals.

$$\min_{\mathcal{L},\mathcal{E}} ||\mathcal{L}||_* + \lambda||\mathcal{E}||_1, \text{ such that } \mathcal{X} = \mathcal{L} + \mathcal{E}, \qquad (4)$$

X denotes the dataset at the pixel level, L represents the invariant component in the time series, and E represents the variable component.

This method can be implemented using the Python package: Tensorly.

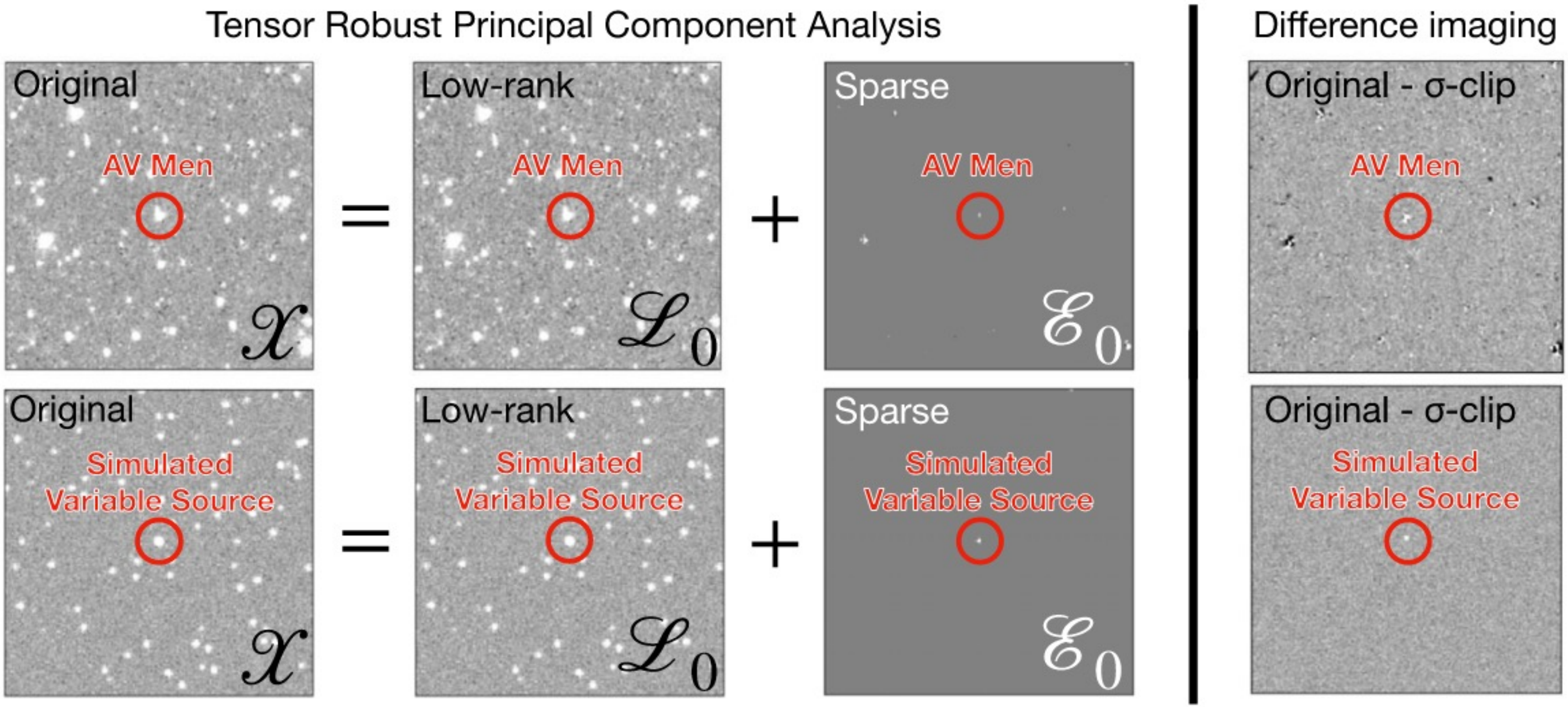


Figure 11. Example of the Tensor Robust Principal Component Analysis (TRPCA, panels on left) and "classical" difference imaging (right panels) on a 201 × 201 pixel WISE image at 4.5 μm. The top row shows the methods applied to our data (shown is one out of the 70 frames). The variable star *AV Men* is clearly identified in the sparse component, while the other non-variable sources appear in the low-rank component. TRPCA suppresses noise and extracts variable sources at a higher significance than difference imaging. However it also detects significant artifacts (likely due to changes in PSF or astrometric alignment between the frames) in the sparse component. The bottom row shows the same method applied on an idealized simulation (real noise, but static PSF and perfect astrometric alignment) with a mock variable source (similar properties as *AV Men* in the center. In this case the TRPCA method returns the location of the simulated variable source without other artifacts.

Summary

1. To search for variable and transient sources, a framework called Annotated Coadds is proposed, executed in two steps: Characterization of Survey Cadence and Pixel-based Variability Metrics.

2. Observational images are mapped onto HEALPix pixels, recording information such as observation time and depth, which allows examination of the number of observations, cadence, and time coverage across different sky regions.

3. For sky regions suitable for variable source searches, pixel-based variability metrics are applied: Reduced Chi-squared, Consecutive Signed-difference Run Length (CSDRL), and Tensor Decomposition.

4. A variability map is constructed for each pixel, providing a visual representation of which sources are variable.