Characterisation of an Exoplanetary System with the GROWTH-India Telescope

Advait Mehla

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1 Introduction

Exoplanets are planets outside our solar system. These are low-intrinsic brightness objects that are situated very close to distant host stars which makes their observations especially challenging. Initially theorised for several centuries, it was thus very hard to detect these. The first confirmed detection of an exoplanet was made in 1992. As of today, there are over 5000 confirmed exoplanets, most of which have been detected by indirect techniques such as the transit and radial velocity methods.

2 Aim

This project aims to detect a transit of one such exoplanet, WASP-43b and characterise its orbital parameters and intrinsic characteristics by fitting the observed light curve to a probabilistic model using specialised software packages. We also aim to demonstrate that exoplanet follow-up is not a task limited to just dedicated exoplanet observatories, and can be feasibly performed by a general purpose transient observatories like the GROWTH-India telescope (Kumar et al., 2022).
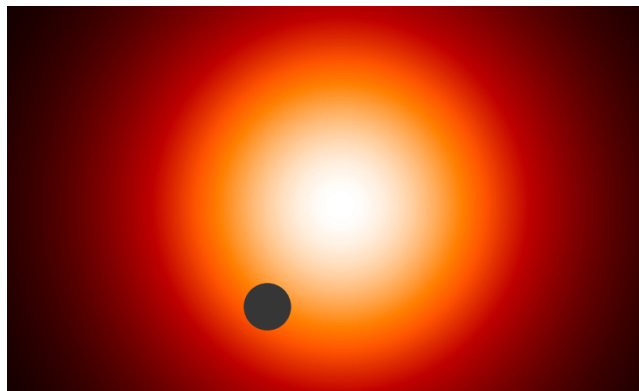

Figure 1: A realistic Python-simulated render of a transit of the WASP-43 system

3   Target

WASP-43 is a star in the Sextans constellation located at a distance of 284 ly from Earth, with $m_V = 12.4$. It hosts one exoplanet, a Hot Jupiter known as WASP-43b (Hellier et al., 2011). Notably, this system has the distinction of being the closest known planet to its host star. Table 1 lists the parameters for this system, along with which of them we assume and which we infer through our analysis.

Parameter	Known Value	Assumed/Inferred
Mass of Star ($M_\star$)	0.72 M$_\odot$	Assumed
Radius of Star ($R_\star$)	0.68 R$_\odot$	Assumed
Limb Darkening Coefficients	$u_1 = 0.601$ $u_2 = 0.149$	Assumed
Radius of Planet (R_p)	0.93 R$_J$	Inferred
Orbital Period (T_{orb})	0.813 d	Inferred
Impact Parameter (b)	0.66	Inferred
Transit Depth	28.9 mmag	Inferred

Table 1: Summary of system parameters (Hellier et al., 2011)

The quadratic limb darkening coefficients for WASP-43 were taken from Gillon et al. (2012), and have been used in our light curve model to accurately ascertain the brightness falloff of the star's surface. The impact parameter, b is defined as the ratio of the apparent distance of the planet from the stellar centre to $R_\star$. It can be expressed in terms of semi-major axis (a), inclination (i) and $R_\star$.

4   Observations

We used the $0.7m$ GROWTH-India Telescope (Kumar et al., 2022) to observe this target. Continuous observations of $60s$ each were made in the r' band from 15:46 to 16:29 UTC on March 24th, 2023. The transit was predicted using the Swarthmore Transit Tracker (Jensen, 2013). We were able to get a few minutes baseline (pre-egress) data but could only observe till the transit midpoint due to a dome error halfway through the session.

5   Photometry

The 30 images obtained from the observations above were processed entirely in Python, using the `Astropy` (Astropy Collaboration et al., 2022) and `Photutils` (Bradley et al., 2022) Python packages. Since the brightness change is of the order of a few milli-magnitudes, regular aperture/PSF photometry is not usable due to large associated errors. Exoplanet data analysis thus utilises relative photometry, where the brightness of the target star is normalised against the variation of non-variable comparison stars available in the field to eliminate errors due to atmospheric conditions.

We identified 6 comparison stars in the field using the AAVSO Variable Star Plotter, and found the counts associated with the target and each of the comparison stars using a circular aperture. The flux of the target was then normalised as mentioned above, and offset to make the baseline 1.0 and plotted in Figure 2.
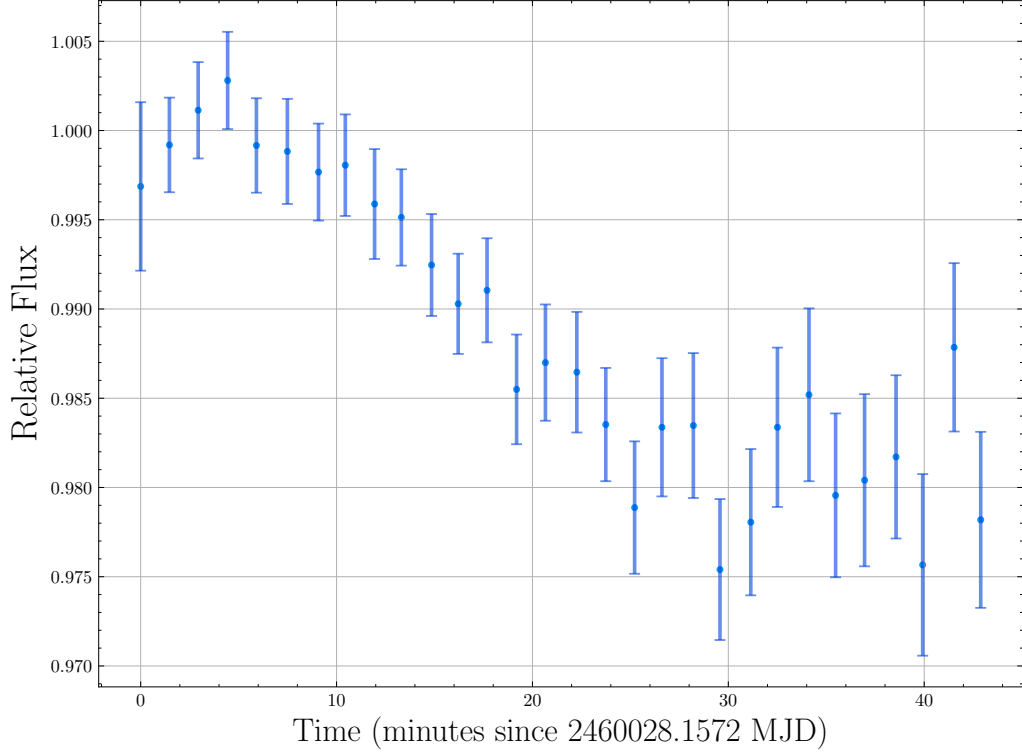
Figure 2: Raw normalised counts of WASP-43b transit

6 Inference

We next proceed to fit the obtained datapoints to a probabilistic transit model. This was done using a Python module, `exoplanet` (Foreman-Mackey et al., 2021). This library utilises `PyMC3` (Salvatier et al., 2016), which is a high-performance inference engine that utilises a variety of advanced Markov chain Monte Carlo (MCMC) methods to fit complex models with many parameters. It also makes use of `STARRY` (Luger et al., 2019) for efficient computation of light curves for a given set of parameters.

MCMC fitting methods rely on the user to supply an informed 'guess' of the parameter space in the form of *prior* probability distribution functions for each of the parameters that need to be inferred. These priors are then randomly and independently sampled and sequentially evolved on the basis of a *likelihood* function which decides the accuracy of a parameter set. This is done by evaluating the model for the current set of parameters and comparing it to the observed data. The parameters are thus evolved over thousands of iterations, leading to empirical probability distribution functions (*posteriors*) for the parameters, thus giving us the required estimates with error bounds.

Parameter	Prior
R_p	$\mathrm{Uniform}(0.06, 0.12)\ \mathrm{R_J}$
T_{orb}	$\exp\left(\mathrm{Normal}(\mu = \log 0.9, \sigma = 0.2)\right)\ \mathrm{d}$
T_{mid}	$\mathrm{Normal}(\mu = 0.75, \sigma = 1)\ \mathrm{h}$
b	$\mathrm{Uniform}(0, 1 + \mathrm{R_p}/\mathrm{R_\star})$

Table 2: Priors for the light curve model

The free parameters in our case were R_p, T_{orb}, b and T_{mid}, the mid-transit time. The priors for the variables are given in Table 2. We tried to keep these sufficiently large and inclusive.
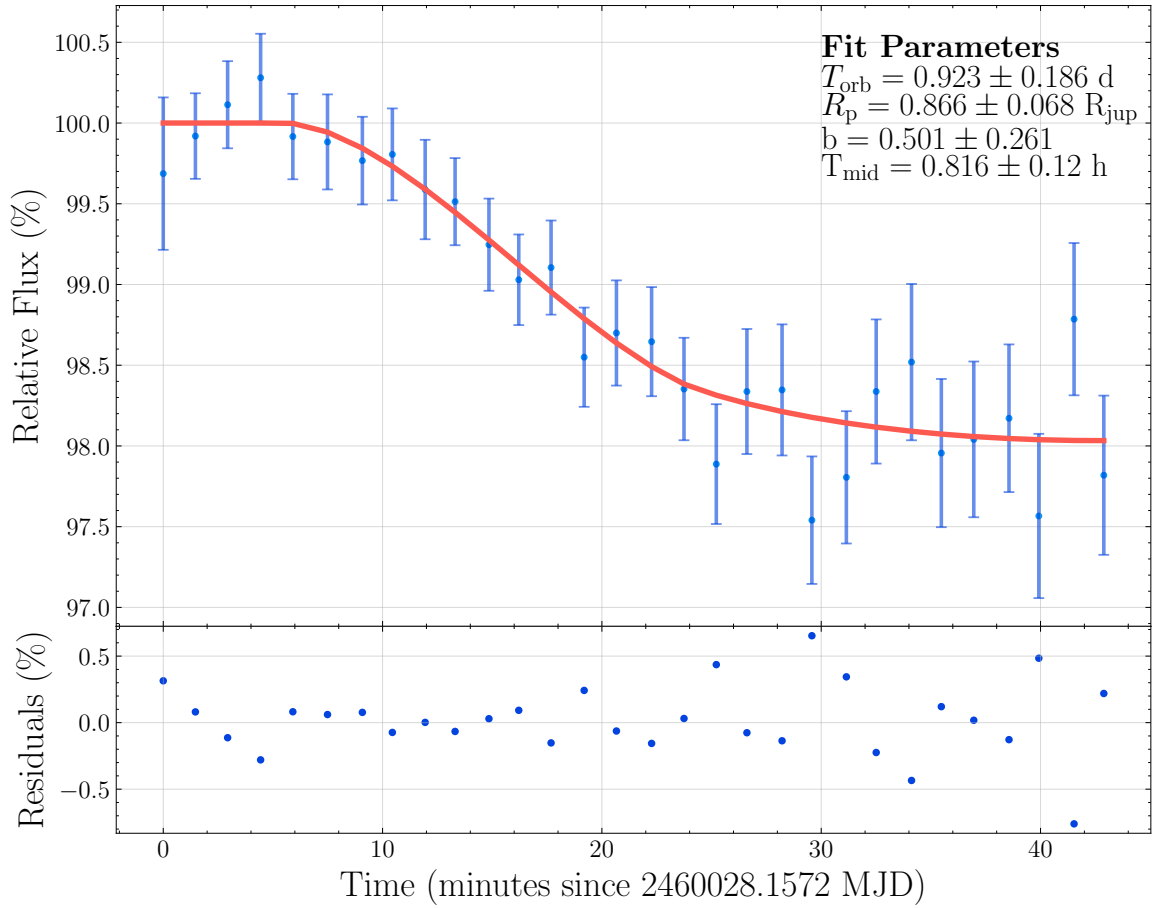
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Figure 3: WASP-43b Fitted Transit Light Curve

The fitted light curve along with parameters can be seen in Figure 3. The obtained values have relatively large error bounds, and this is due to us having observed only the first half of the transit. The full posterior distribution can also be visualised as a corner plot (Foreman-Mackey, 2016) showing pairwise join distributions, as seen in Figure 4.

7   Results

Table 3 lists our results with 1σ error bounds and compares them to known values. As we could only observe half the transit, the error bars are quite large. But the known values are still within 1σ of the mean posterior value, which is a good indicator of the reliability of this method. In conclusion, GIT can be viably used for the confirmation or follow-up of smaller exoplanets using relative photometry and modern, efficient MCMC algorithms for inference.

Parameter	Known Value	Inferred Value
Radius of Planet (R_p)	0.93 R_J	$0.856^{+0.077}_{-0.058}$ R_J
Orbital Period (T_{orb})	0.813 d	$0.908^{+0.198}_{-0.169}$ d
Mid-transit time (T_{mid})	45 min	$48.96^{+5.76}_{-8.64}$ min
Impact Parameter (b)	0.66	$0.538^{+0.248}_{-0.358}$

Table 3: Fitted parameters compared to known values from Hellier et al. (2011)
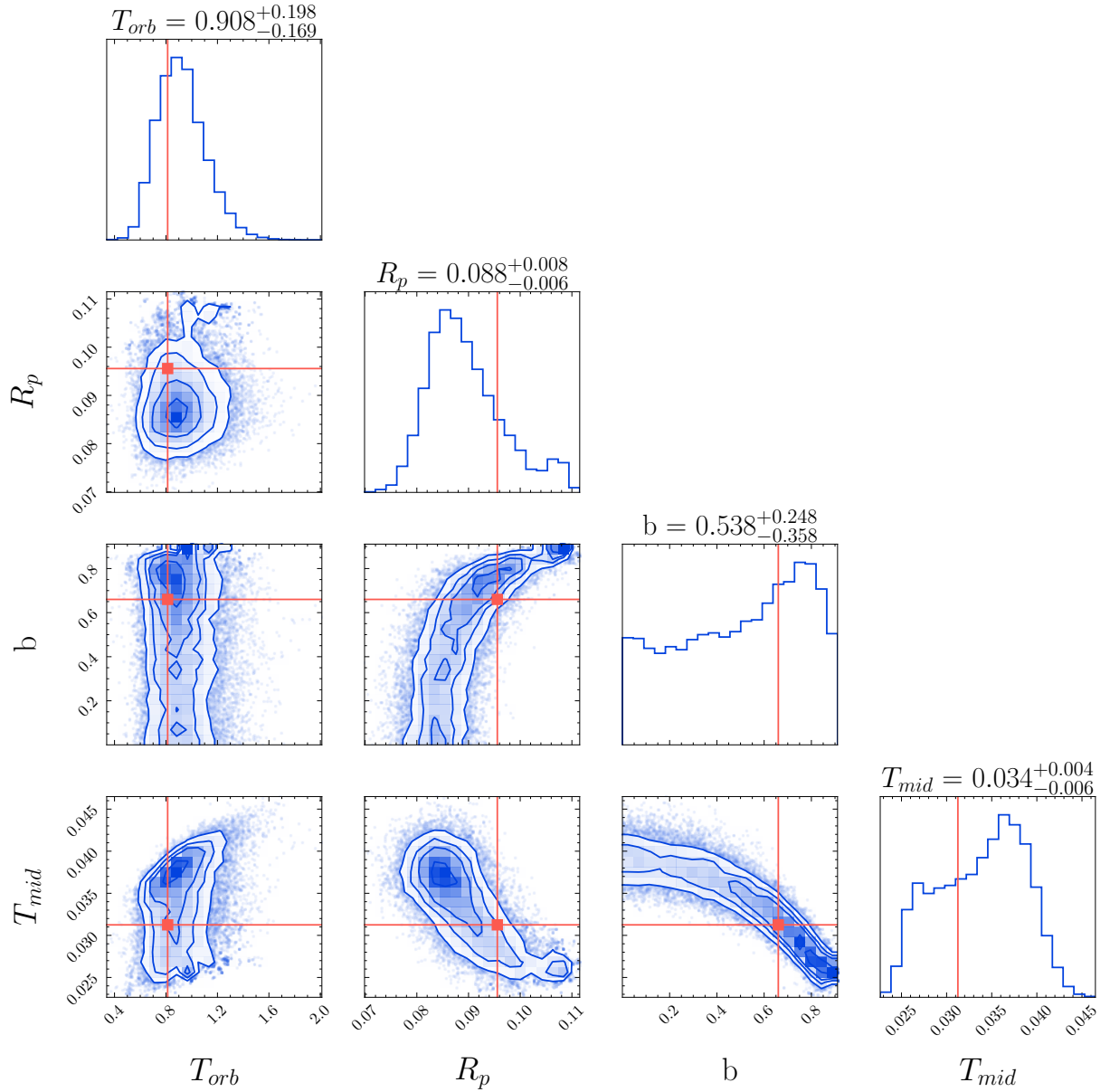
Figure 4: Joint distributions of parameter posteriors. The red lines mark true values.

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