High-contrast Thermal Infrared Spectroscopy with ALES: The 3–4 μm Spectrum of κ Andromedae b

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Abstract

We present the first L-band (2.8–4.1 μm) spectroscopy of κ Andromedae b, a ∼20 M_Jup companion orbiting at 1″ projected separation from its B9-type stellar host. We combine our Large Binocular Telescope (LBT) Arizona Lenslets for Exoplanet Spectroscopy (ALES) integral field spectrograph data with measurements from other instruments to analyze the atmosphere and physical characteristics of κ And b. We report a discrepancy of ~20% (2σ) in the L′ flux of κ And b when comparing to previously published values. We add an additional L′ constraint using an unpublished imaging data set collected in 2013 using the LBT Interferometer/LMIRCam, the instrument in which the ALES module has been built. The LMIRCam measurement is consistent with the ALES measurement, both suggesting a fainter L-band scaling than previous studies. The data, assuming the flux scaling measured by ALES and LMIRCam imaging, are well fit by an L3-type brown dwarf. Atmospheric model fits to measurements spanning 0.9–4.8 μm reveal some tension with the predictions of evolutionary models, but the proper choice of cloud parameters can provide some relief. In particular, models with clouds extending to very low pressures composed of grains ≤1 μm appear to be necessary. If the brighter L′ photometry is accurate, there is a hint that subsolar metallicity may be required.

Universe, a dwarf extragalactic stellar remnant, is 5.25 billion light-years away. The stars and planets that are not part of the central galaxy are generally thought to have formed elsewhere and have since undergone gravitational interactions with the parents of the stars. The discovery of planets orbiting stars other than the Sun, known as exoplanets, has revolutionized our understanding of the solar system and the potential for life beyond our own. The ε Eridani system, for example, is only 10 light-years away and consists of a B0-type star with three confirmed planets, two of which have masses similar to that of Jupiter.

1 Introduction

The κ And system consists of a late B-type star orbited by a substellar companion at ∼1″ projected separation (~50 au; Carson et al. 2013). The mass of the companion, ∼20 M_Jup (e.g., Uyama et al. 2020) is estimated by combining evolutionary models (e.g., Baraffe et al. 2015), constraints on the bolometric luminosity (Bonfey et al. 2014), and an age estimate for the system (Bonfey et al. 2014; Jones et al. 2016).

Age dating early-type stars like κ And is challenging. However, if the early-type star is a member of a kinematic association that has later-type stars whose ages can be more definitively determined, more constrained age estimates are possible. The kinematics of the κ And system are suggestive of membership in the Columba young association (Zuckerman et al. 2011; Carson et al. 2013; Bonfey et al. 2014), which has an age of 42±4 Myr (Bell et al. 2015). Bonfey et al. (2014) report a 95% chance that κ And is part of the Columba young association (using the online tool reported in Malo et al. 2013). Using the same analysis, Bonfey et al. (2014) report a 98% chance that the four-planet HR 8799 system is a member of Columba, implying that the two systems are siblings. However, using astrometric constraints provided by Gaia DR2 (Gaia Collaboration et al. 2018) and the online BANYAN 2.07 tool (which supercedes the Malo et al. 2013 version; Gagné et al. 2018), there is a 31% chance that κ And is a member of Columba and a 42% chance for HR 8799. Yet, youth, and membership in the young association, is supported for both objects by comparison to evolutionary models. This is typically an imprecise exercise for early-type stars, but both stars have had their photospheres resolved with long-baseline optical interferometry, meaning their fundamental parameters are particularly well constrained and model comparisons more precise (Baines et al. 2012; Jones et al. 2016). For κ And the age constraint from evolutionary models is 47±7 Myr, consistent with membership in Columba.

While the planetary nature of the HR 8799 companions is secure—masses estimated to be below the deuterium burning limit, system architecture comprising coplanar nonhierarchical orbits—the nature of κ And b is more uncertain. On the one hand, the estimated mass of κ And b is larger than the deuterium burning limit. On the other hand, the mass ratio with κ And A (M_b = 2.8 M_Jup; Jones et al. 2016) is almost identical to the star/planet mass ratios (~0.7%) within the HR 8799 system. Consequently, the κ And system provides an excellent target to study the formation of objects in the low-mass brown dwarf/high-mass planet regime where objects of similar mass can have distinct formation histories (e.g., Brandt et al. 2014; Reggiani et al. 2016; Wagner et al. 2019).

The eccentricity of the κ And b orbit, recently refined by Uyama et al. (2020), is more likely to be drawn from the brown dwarf population than the planetary population according to recent work by Bowler et al. (2020). However, the system is part of the sample that Bowler et al. (2020) used to constrain the eccentricity distributions. When constructing eccentricity

7 Hubble Fellow.
8 http://www.exoplanet.esa.int/banyan/banyansigma.php
distributions using mass ratio bins rather than mass bins to define the populations, Bowler et al. (2020) include \( \kappa \) And b in the planetary group and the distinction between the eccentricity distributions becomes more ambiguous.

Atmospheres provide an avenue for constraining companion composition, which can help distinguish formation processes. For example, the binary star formation mechanism results in similar composition for both components (Desidera et al. 2006), but the planet formation process can naturally enhance the metallicity of a planet over that of the host star (e.g., Pollack et al. 1986; Wong et al. 2004; Boley et al. 2011). As a result, differential metallicity is one potential route to distinguish formation processes.

The metallicity of a planet over that of the host star (distributions using mass ratio bins rather than mass bins to constrain is large for young low-mass objects (e.g., Barman et al. 2011a; Skemer et al. 2011; Marley et al. 2012) making metallicity constraints challenging due to model degeneracies connecting temperature, gravity, chemistry, and cloud properties (e.g., Rajan et al. 2017). Overcoming these degeneracies is particularly challenging due to the complex nature of clouds and atmospheric condensates.

Breaking these degeneracies benefits from measurements covering a wide range of wavelengths (e.g., Stephens et al. 2009; Morzinski et al. 2015; Skemer et al. 2016). In this paper we report the first \( L \)-band (2.8–4.1 \( \mu \)m) spectroscopy of \( \kappa \) And b, harnessing the new thermal-infrared integral field spectroscopy capabilities delivered by the Arizona Lenslets for Exoplanet Spectroscopy (ALES) instrument embedded within LMIRCam (Skrutskie et al. 2010; Leisenring et al. 2012) and operating within the Large Binocular Telescope Interferometer (LBTI) architecture (Skemer et al. 2015, 2018a). We targeted \( \kappa \) And b with ALES to increase the wavelength range over which spectroscopic measurements probe the atmosphere of the object. In Section 2 we describe our observations. We discuss our data reduction approach in Section 3. In Section 4 we present our results and describe our approach to fitting model atmosphere spectra to ALES data combined with measurements from other instruments spanning from 0.9 to 5 \( \mu \)m. In Section 5 we provide a discussion of our results focusing on the contribution to the fit provided by ALES.

2. Observations

We observed the \( \kappa \) Andromedae system on UT 2016 November 13, using LBTI/ALES in its 2.8–4.1 \( \mu \)m mode with a spectral resolution of \( R \sim 20 \). The median seeing was 1"*, varying between 0"8 and 1"2. We used only the left side of the LBT aperture and adaptive optics system, correcting 400 modes with the deformable secondary at 1 kHz loop speed. Thin cirrus were present and atmospheric transmission was poor short of 3.4 \( \mu \)m due to telluric water-ice absorption.

During our observations, LBTI/ALES was in the process of a multistep upgrade and in an intermediate state, delivering a grid of 74 \( \times \) 86 spaxels covering a 1"93 \( \times \) 2"24 field of view (0"026 spaxel\(^{-1}\)). In this early implementation, ALES spaxels were affected by strong off-axis astigmatism, delivering significantly worse data near the edges of the field. The lenslet array has since been upgraded (Hinz et al. 2018; Skemer et al. 2018a).

We observed using a three-point nod pattern alternating from a position with the primary star centered on the lenslet array (10 frames), to a position with the companion centered on the array (60 frames), then to a nearby sky position (60 frames). This approach ensured that \( \kappa \) And b was always observed through a region of high optical quality even as its position rotated in the frame with the parallactic angle (Stone et al. 2018). We chose a 1.16 s exposure time to keep the sky emission in the linear range of the HAWAII-2RG detector.

In all, we executed 16 three-point nod cycles, collecting 18.5 minutes of exposure time with the companion positioned in the region of the ALES field of view with low astigmatism. These data include 138° of parallactic angle change.

Immediately following our companion observations, we collected unsaturated frames of the primary star using 0.58 s exposures. These data were used for simultaneous telluric and photometric calibration, described below. For wavelength calibration, we observed a nearby sky position through four narrowband (\( R \sim 100 \)) filters positioned upstream of the ALES optics within LMIRCam (Stone et al. 2018). At the thermal-infrared wavelengths where ALES operates, the blank sky provides plenty of flux through the narrowband filters so that wavelength calibration can be carried out efficiently.

3. Data Reduction

3.1. Making Data Cubes

The detector used by ALES exhibits time-variable offsets within each 64-column readout channel due to drifting biases in the readout amplifiers. We correct for this by measuring the offset in each channel using a median of the pixels in the first 20 rows—the extent of the detector not covered by the ALES lenslet array. We found that this approach provided a better correction compared to using only the four overscan rows of the detector. After channel offset correction, we corrected bad pixels by replacing them with the median of their nearest four good neighbors.

For each three-point nod cycle, we median combined the (10 primary, (60) companion, and (60) sky frames. We then subtracted the median sky frame from the median on-source images. We extracted \((x, y, \lambda)\) data cubes using an inverse variance and spatial profile weighted extraction approach on each of the 74 \( \times \) 86 microspectra across the ALES field (Horne 1986; Brieseheimer et al. 2018). Since our lenslet array was paired with a pinhole grid to alleviate cross-talk due to diffraction (Skemer et al. 2015), we noticed that the spatial profile of each microspectro was not a strong function of wavelength. Consequently, to measure the spatial profile of each microspectro, we first collapsed each microspectro along the wavelength axis to create a single high signal-to-noise spatial profile which we then applied at all wavelengths. A typical spatial profile had \( \sim 5 \) HAWAII-2RG pixels FWHM. Our cubes included 38 wavelength slices spanning 2.85–4.19 \( \mu \)m.

Resulting spectral image cubes revealed a point-spread function (PSF) having 4.1 spatial pixels FWHM at 3.77 \( \mu \)m.

3.2. High-contrast Spectral Extraction

The superb performance of the LBT-AO system and the sensitivity of ALES within LMIRCam combined to reveal \( \kappa \) And b in each of our 16 individual cubes. As a result, aggressive software post-processing to separate the companion from the primary star was not necessary, and we avoided all but
the most simple approach in order to minimize the introduction of hard-to-calibrate spectrophotometric biases (e.g., Lafrenière et al. 2007; Pueyo 2016). Working on each wavelength slice independently (no spectral differential imaging), we applied an unsharp mask high-pass spatial filter using a Gaussian smoothing kernel with \( \sigma = 2 \) pixels (52 milliarcsecond) and then a basic angular differential imaging (ADI) algorithm. Our ADI approach involved subtracting from each image at wavelength \( \lambda \) the median of all other images with wavelength \( \lambda \). The closest any two images were in parallactic angle was 3°, implying a minimum displacement of \( \frac{\lambda}{D} \) at the separation of the companion. The final processed images for each wavelength are summed for presentation in Figure 1.

When using ADI-based image processing algorithms, extra care must be given to photometric measurements to avoid biases related to source self-subtraction. We injected a scaled negative version of the wavelength-dependent PSF into each image slice at the position of the companion (e.g., Lafrenière et al. 2007; Pueyo 2016). The scale factor and source position were fitted simultaneously using the residuals after ADI processing to define the goodness of fit. For this purpose, we used the unsaturated data cube of \( \kappa \) And A for our wavelength-specific PSFs. With this approach, our extracted spectrum is automatically corrected for telluric absorption, since it is present in both the PSF and companion. To flux calibrate our extracted spectrum we multiplied by a NEXTGEN (Hauschildt et al. 1999) model A0 spectrum appropriately scaled to yield the observed \( L' \) flux of \( \kappa \) And A (\( m_{L'} = 4.32 \); Bonnefoy et al. 2014). An A0 star model is a close approximation to the B9 spectral type of \( \kappa \) And A at these wavelengths.

Photometric uncertainty was estimated using the bootstrap method, repeating our extraction and calibration procedure 30 times, each time selecting a different random sample (with replacement) of our 16 frames (Press et al. 2002). We provide our extracted spectrum in Table 1.

4. Analysis

4.1. Tension with Earlier \( L' \) Measurements

As a consistency check, we compared the magnitude of \( \kappa \) And b implied by our flux-calibrated spectrum to previously reported photometry. To do this, we used the NIRC2 Lp filter curve to compare our measurement to that of Bonnefoy et al. (2014), revealing a 2\( \sigma \), 0.2 mag, discrepancy—the ALES spectrum (with \( m_{L'} = 13.32 \pm 0.07 \)) being fainter than the reported NIRC2 measurement (with \( m_{L'} = 13.1 \)). The NIRC2 measurement reported by Bonnefoy et al. (2014) is consistent with the Infrared Camera and Spectrograph (IRCS) measurement of \( \kappa \) And b reported by Carson et al. (2013). For an additional check, we compared to an unpublished LBTI/LMIRCam \( L' \) observation of \( \kappa \) And collected on UT 2013 October 24 as part of the LBTI Exozodi Exoplanet Common Hunt (LEECH) survey (Stone et al. 2018). The data cover 97° of parallactic rotation and were collected using only the right-side 8.4 m mirror of the LBT. Unsaturated images of the primary star were obtained using a neutral density filter at the end of the observing block. Preprocessing of the LMIRCam data followed the steps outlined in Stone et al. (2018), and high-contrast photometry was carried out exactly as described above for a single wavelength slice of an ALES cube. The LMIRCam data yield \( m_{L'} = 13.36 \),

| Wavelength (\( \mu \text{m} \)) | \( F_{L'} \) (mJy) | \( \sigma_{F_{L'}} \) (mJy) |
|-----------------------------|----------------|---------------------|
| 2.85                        | 0.88           | 0.37                |
| 2.91                        | 0.87           | 0.20                |
| 2.96                        | 0.76           | 0.21                |
| 3.02                        | 0.65           | 0.27                |
| 3.06                        | 1.07           | 0.35                |
| 3.11                        | 0.92           | 0.51                |
| 3.16                        | 1.06           | 1.40                |
| 3.20                        | 0.89           | 0.48                |
| 3.25                        | 1.31           | 0.28                |
| 3.29                        | 1.05           | 0.16                |
| 3.33                        | 1.07           | 0.14                |
| 3.37                        | 0.86           | 0.15                |
| 3.41                        | 1.13           | 0.11                |
| 3.45                        | 1.18           | 0.07                |
| 3.49                        | 1.04           | 0.07                |
| 3.53                        | 1.12           | 0.09                |
| 3.57                        | 1.15           | 0.09                |
| 3.60                        | 1.15           | 0.08                |
| 3.64                        | 1.19           | 0.06                |
| 3.67                        | 1.24           | 0.08                |
| 3.71                        | 1.27           | 0.07                |
| 3.74                        | 1.25           | 0.08                |
| 3.77                        | 1.18           | 0.08                |
| 3.81                        | 1.20           | 0.07                |
| 3.84                        | 1.31           | 0.09                |
| 3.87                        | 1.30           | 0.11                |
| 3.90                        | 1.19           | 0.10                |
| 3.93                        | 1.30           | 0.11                |
| 3.96                        | 1.19           | 0.07                |
| 3.99                        | 1.21           | 0.11                |
| 4.02                        | 1.14           | 0.11                |
| 4.05                        | 1.02           | 0.10                |
| 4.08                        | 1.06           | 0.12                |
| 4.11                        | 1.14           | 0.13                |
| 4.14                        | 1.05           | 0.19                |

Figure 1. ALES image of \( \kappa \) And b made by summing the \((x, y, \lambda)\) data cube over the wavelength dimension.
consistent with the ALES spectrum. Thus, NIRC2 and IRCS suggest \( \kappa \) And b has \( m_L' = 13.1 \) whereas LMIRCam imaging and ALES give \( m_L' = 13.3 \).

Since all four data sets were taken at different times, we address whether variability could play a significant role in the 20% flux discrepancy among the measurements: it cannot. Low-gravity early L-type objects typically vary by \( \lesssim 1\% \) (Metchev et al. 2015; Vos et al. 2020). Even the most extreme L-type variables exhibit only \( \sim 5\% \) photospheric variability in the thermal-infrared, and these are of later spectral type than \( \kappa \) And b (see Zhou et al. 2020).

The most conspicuous difference between the earlier \( L' \) photometry and the measurements reported here, is that we used \( \kappa \) And A as a photometric calibrator for \( \kappa \) And b, while Carson et al. (2013) and Bonnefoy et al. (2014) both use HR 8799 A. We take \( m_{L'} = 4.32 \) for \( \kappa \) And A from Bonnefoy et al. (2014). Another significant difference is that we used negative source injections to account for the throughput of our high-contrast image processing approach, while both Carson et al. (2013) and Bonnefoy et al. (2014) use aperture photometry corrected with a throughput factor. Additional \( L' \) photometry of the system, including of the primary, is warranted for a more accurate \( L' \) flux scaling of \( \kappa \) And b.

While the photometry differs by only 2\( \sigma \), the difference is large enough to affect the best-fit atmospheric model parameters (see below). Therefore, we elect to fit models to the spectral energy distribution (SED) of \( \kappa \) And b using both the Carson et al. (2013) value (\( m_{L'} = 13.1 \)) and the ALES value (\( m_{L'} = 13.3 \)).

### 4.2. Fits to Brown Dwarf Template Spectra

We compiled a set of brown dwarf spectra, covering spectral types M9 through T5, to compare to \( \kappa \) And b. The brown dwarf data come from the Spex instrument and are collected from Cushing et al. (2008) and Rayner et al. (2009). The selected spectra were chosen for their wavelength coverage, extending to 4.1 \( \mu \)m. We do not have access to a large number of objects with this broad wavelength coverage. Future \( L- \) and \( M- \)band spectroscopy of brown dwarfs, covering a wide range of spectral types and surface gravities, will be important for facilitating empirical comparisons to the spectra of directly imaged companions both for future ALES data sets and in the era of similar more powerful instruments on giant segmented mirror telescopes (e.g., Mid-Infrared ELT Imager and Spectrograph and Planetary Systems Imager 2–5 micron instrument; Brandl et al. 2014; Skemer et al. 2018b). The James Webb Space Telescope will play an important role in delivering empirical brown dwarf spectra spanning near- to mid-infrared wavelengths.

For the comparison, we combined our new \( L- \)band ALES spectrum of \( \kappa \) And b with the \( y- \)band spectrum from P1640 (Hinkley et al. 2013), and the \( J- \), \( H- \), and \( K- \)band spectrum from CHARIS (Currie et al. 2018). We flux calibrate the \( y- \)band photometry reported in Uyama et al. (2020).

To fit the template spectra to the composite 0.9–4.1 \( \mu \)m integral field spectrograph (IFS) spectrum of \( \kappa \) And b, we first smoothed the Spex spectra to match the resolving power of the three integral field spectrographs, \( R \sim 20 \). We propagated the noise in the Spex spectra through this process by sampling the (assumed Gaussian) noise of each data point and repeating the smoothing process 100 times. The standard deviation of the resulting spread in the \( R = 20 \) Spex spectra was taken as the error.

We then used a \( \chi^2 \) fitting approach to find the best match, using

\[
\chi^2 = (f - sM)^T \Sigma^{-1}(f - sM),
\]

where \( f \) is the observed spectrum, \( M \) is the template spectrum, \( s \) is a scale factor to accommodate sources at different distances and with different radii, and \( \Sigma \) is the data covariance matrix. We construct \( \Sigma \) as a block diagonal matrix, with a block encoding the P1640 covariance, a block encoding the CHARIS covariance, and a block encoding the ALES covariance. For ALES, we determine the covariance using the method of Greco & Brandt (2016), deriving \( A_{\rho} = 0.1, \sigma_{\rho} = 0.16, A_{\delta} = 0.25, \sigma_{\delta} = 0.01, \) and \( A_{\phi} = 0.64, \) with variables as defined by those authors. We take the CHARIS block to be diagonal, which is a good approximation for these data (Currie et al. 2018). The P1640 data are not as aggressively binned as the CHARIS data, and like the ALES spectrum, neighboring spectral channels appear correlated. Hinkley et al. (2013) do not provide a measured covariance matrix for the P1640 data, so in order to down weight the correlated data points from the P1640 spectrum, we use the same empirical correlation parameters as determined for the ALES spectrum and apply them to the P1640 data to create a covariance matrix. Using this P1640 covariance matrix did not change the resulting fit compared to assuming an uncorrelated error within the P1640 block. Finally, we added to the diagonal of \( \Sigma \) the variance due to uncertainty in the template spectra.

We performed the fit for three scenarios: (1) assuming \( m_{L'} = 13.3 \), as measured by ALES and LMIRCam; (2) assuming \( m_{L'} = 13.1 \), as measured by the IRCs and NIRC2 instruments; and (3) for the \( m_{L'} = 13.1 \) case, in addition to
fitting for the best template, we also fit for the best reddening parameters using the model of Cardelli et al. (1989) to modify each template. This last method is motivated by Hiranaka et al. (2016) who show that high-altitude hazes in the atmospheres of brown dwarfs can mimic the effect of interstellar reddening on the emergent spectrum.

In Figure 2 we show how the resulting $\chi^2$ varies as a function of spectral type for each scenario. In Figure 3 we show the best-fitting template spectrum for all cases. The best-fit L3-type object, 2MASS J15065441+1321060, is the same for each case and is also the best-fitting field-gravity template found by Uyama et al. (2020) who fit y-band photometry and the CHARIS near-infrared spectroscopy. Cushing et al. (2008) fit synthetic models to the spectrum of 2MASS J15065441+1321060 and report $T_{\text{eff}} = 1800$ K and log$(g) = 4.5$.

The best fit is for the $m_L = 13.3$ case, the SED of $\kappa$ And b appearing consistent with a typical field L3. The most significant discrepancy between the high-contrast companion and the brown dwarf spectra is seen in the last few spectral channels at the longest wavelengths. These wavelengths, near the edge of the atmospheric transmission window, can be affected by observing conditions.

For the case of $m_L = 13.1$, the near-infrared to thermal-infrared color is too red. Applying an interstellar reddening prescription (Cardelli et al. 1989) can improve the fit somewhat, but the fitter is not at liberty to choose a strong enough reddening to accommodate the thermal-infrared to near-infrared colors because such a large value would change the ratios between the near-infrared bands, which are very precisely constrained by the CHARIS data. Red near-infrared to thermal-infrared color in L-dwarf spectra is known to correlate with low surface gravity (e.g., Filippazzo et al. 2015).

4.3. Fits to Model Atmospheres

We fit the SED of $\kappa$ And b to model spectra to better understand the physical nature of the atmosphere of the high-contrast companion. Many previous studies fit synthetic spectra to observations of $\kappa$ And b using a variety of observational constraints covering different wavelength ranges and a variety of model atmosphere implementations. Table 2 summarizes the best-fit models from previous studies found in the literature. Best-fit model atmosphere parameters span a temperature range consistent with spectral type determined by comparison to brown dwarf spectra.

For the purposes of fitting synthetic models, we use the IFS spectra covering 0.9–4.1 $\mu$m described in Section 4.2 and combine with LBTI/LMIRCam $M'$-band photometry from Bonnefoy et al. (2014). We also expand the covariance matrix $\Sigma$ by one-dimension and add a new 1 x 1 block to the diagonal to account for the measurement uncertainty in the $M'$-band flux. We then use Equation (1) as the goodness-of-fit metric to identify the best model parameters as constrained by the data. In this case we take the scale factor

$$s = (Rq)^2,$$

where $R$ is the radius of the object (to be fit), and $q$ is the parallax of the $\kappa$ And system, taken to be 19.98 milliarcseconds (Gaia Collaboration et al. 2018).

The models we use are an extension of those described in Barman et al. (2011b, 2015) and Miles et al. (2018). Specifically, we can tune both the cloud-top pressure (below which, climbing to higher altitudes, cloud particles decay exponentially) and the median particle size within clouds. The models used here reach even lower cloud-top pressures and smaller median particle sizes than previous studies. As we show below, these parameters appear important for fitting the observations of young, cloudy L dwarfs. Table 3 provides the parameter ranges of the models we used to fit our data.

In Figure 4 we show all the models allowed at the 95% confidence level for the case where the ALES spectrum corresponds to $m_L = 13.3$. Taking $\Delta \chi^2$ to be $\chi^2$-distributed with five degrees of freedom (the four atmospheric model parameters in Table 3 and the object radius, which is simultaneously fit), these are all the models with $\Delta \chi^2 < 11.3$.

We see the best-fit models break into two categories, a set with $T_{\text{eff}} = 1900$ K and a set with $T_{\text{eff}} = 1500$ K. This is reminiscent of the multimodal $\chi^2$ surfaces seen in previous fits to early L-type objects (e.g., Stone et al. 2016).
In Figure 5 we show the best-fit model atmosphere for the case where we scale the ALES spectrum to provide $m_L' = 13.1$. For this case, only one model is allowed at 95% confidence, having $T_{\text{eff}} = 1900 \text{ K}$, $\log(g) = 5.5$, high-altitude clouds (cloud-top pressure of $10^5 \text{ dyne cm}^{-2}$), and small grain sizes (0.25 μm median).

In both Figures 4 and 5, error bars on the CHARIS data (taken from Currie et al. 2018) are smaller than the plotting symbols. These tiny error bars strongly influence the fit; small changes in the shape of the near-infrared spectrum can drive huge changes in the $\chi^2$. The result is a narrow range of parameters formally allowed by the data. For example, Figure 4 shows only four models within $\Delta \chi^2$ of 11.3 from the best-fit model—the 95% confidence range for a model with five parameters. However, if we scale up the CHARIS errors to have the same average fractional variance as the ALES
spectrum, then the fitter allows 19 models within 95% confidence, spanning $T_{\text{eff}}$ in Kelvin; surface gravity, $g$, in cm s$^{-2}$; cloud-top pressure, ctp, in dyne cm$^{-2}$; median cloud particle size, gs, in microns; and object radius, $R$, in $R_{\text{Jup}}$. Our best-fit model from the set indicated in Table 3 (solid teal green curve) appears in each panel. Upper panel: the best-fit models reported by Bonnefoy et al. (2014) and Uyama et al. (2020) are shown with dashed curves. These are not fits to the data shown, but are simply taken from previous works and plotted. Second from top: the best-fit model has high surface gravity that is unphysical. A model with surface gravity more consistent with the predictions of evolutionary models is shown, but it is too blue in its near-infrared to $L$-band colors. Third from top: a cooler low-gravity model better matches the gross colors of the data, but misses the shape of the $K$-band peak. Bottom: a cooler low-gravity model with subsolar metallicity provides a plausible match to the data.

In all cases, clouds extending to very low pressures (high altitudes) are preferred by the fit. As cloud extent—and opacity—increases, molecular bands in the emergent spectrum are muted and the emission trends toward a blackbody shape. For example, Morzinski et al. (2015) showed for β Pic b that fitting a blackbody spectrum to photometry covering the 0.99–4.8 μm SED of the $T_{\text{eff}} \sim 1700$ K planet provides a better fit than multiple more sophisticated atmosphere models. We fit blackbody models to the measured portion of the $\kappa$ And b SED, as shown in Figure 6. Models spanning temperatures from 1900 K to 2200 K provide good fits (95% confidence interval), with slightly cooler, but overlapping, temperatures for the $m_L = 13.1$ case. The blackbody implied radii range from 0.94 to 1.25 $R_{\text{Jup}}$. For $\kappa$ And b, the blackbody models always yield worse fits than the atmosphere models described above, partly demonstrating the strength of spectroscopy over photometry (the near-infrared water bands are clearly seen in the CHARIS data), and partly indicating the good performance of our cloudy models.

4.3.1. Estimating $L_{\text{bol}}$

Bolometric luminosity can be constrained using measurements of the SED covering a broad wavelength range. With enough measurements, luminosity estimates are robust to the choice of atmospheric model used to interpolate between and extrapolate beyond the measured portions of the SED, yielding a robust value (see Table 4).

We combine the 0.9–4.8 μm measurements of $\kappa$ And b together with the well-fit (95% confidence) model atmospheres to estimate the bolometric luminosity of the object. To do this, we used the synthetic atmosphere models to extrapolate the

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Figure 5. Synthetic atmosphere model spectra compared to the 0.9–4.8 μm SED of $\kappa$ And b with the $L$-band flux scaling consistent with Subaru and Keck photometry. Star symbols on synthetic spectra indicate sampled fluxes compared to the observed data. Model atmosphere $T_{\text{eff}}$ in Kelvin; surface gravity, $g$, in cm s$^{-2}$; cloud-top pressure, ctp, in dyne cm$^{-2}$; median cloud particle size, gs, in microns; and object radius, $R$, in $R_{\text{Jup}}$. Our best-fit model from the set indicated in Table 3 (solid teal green curve) appears in each panel. Upper panel: the best-fit models reported by Bonnefoy et al. (2014) and Uyama et al. (2020) are shown with dashed curves. These are not fits to the data shown, but are simply taken from previous works and plotted. Second from top: the best-fit model has high surface gravity that is unphysical. A model with surface gravity more consistent with the predictions of evolutionary models is shown, but it is too blue in its near-infrared to $L$-band colors. Third from top: a cooler low-gravity model better matches the gross colors of the data, but misses the shape of the $K$-band peak. Bottom: a cooler low-gravity model with subsolar metallicity provides a plausible match to the data.
SED to shorter and longer wavelengths and to interpolate between the measured bands. We then integrated the semi-empirical SED and used the Gaia parallax to calculate the luminosity. To account for measurement uncertainties we calculated the luminosity 20 times, each time sampling \( \Sigma \), the data covariance matrix, to modify the measured values, rescaling the atmosphere model to fit each realization. The results are presented in Table 4. We can estimate the scale of systematic error due to the choice of atmosphere model and \( L \)-band flux scaling by noting the range of luminosities measured for all cases. We determine that the luminosity of \( \kappa \) And b is in the range \( \log_{10}(L/L_\odot) = -3.69 \) to \(-3.78\).

### 5. Discussion

Evolutionary models provide a way to evaluate the quality of atmospheric fits and to distinguish physically reasonable atmospheric parameters from fits that are hard to square with our understanding of the early evolution of substellar objects.

The behavior of evolutionary models at young ages (\(<100\) Myr) depends sensitively on assumptions about the initial entropy of objects (Marley et al. 2007) but not on the choice of atmospheric model used to calculate surface energy losses. Consequently, once initial entropy and age are fixed, parameters predicted by evolutionary models, such as luminosity and radius (and derivative quantities like effective temperature and surface gravity) are robust—modulo additional parameters effecting the internal physics of the body, such as composition.

For \( \kappa \) And b we fix initial entropy by considering hot-start models exclusively. Hot-start evolutionary models are consistent with the luminosity and age range of \( \kappa \) And b (Bonnefoy et al. 2014) and are theoretically supported given the large accretion rates required to build a \( \sim 20 M_{\odot} \) object during the lifetime of a typical B-star protostellar disk (e.g., Mordasini 2013; Cumming et al. 2018).

The results of Bell et al. (2015) and Jones et al. (2016) suggest an age of \( \sim 50 \) Myr for \( \kappa \) And. We choose a conservative age range of 10–100 Myr, and use the luminosity constraints shown in Table 4 to compare to the hot-start solar metallicity evolutionary model predictions of Chabrier et al. (2000).

#### Table 4

| Model\(^a\) | \( L_{bol} \) (\( \% \)-Measured\(^b\)) |
|---|---|
| \( m_{1/3} = 13.3 \) Synthetic Atmosphere Models | \( L_{bol} \) | \%| Measured\(^b\) |
| (1900, 5.0, 1E5, 0.25, 1.11 \( \pm \) 0.01) | \( -3.78 \pm 0.01 \) | 63% |
| (1900, 4.5, 1E5, 0.25, 1.14 \( \pm \) 0.01) | \( -3.78 \pm 0.01 \) | 64% |
| (1500, 5.0, 5E5, 1, 2.05 \( \pm \) 0.02) | \( -3.71 \pm 0.01 \) | 54% |
| (1500, 4.5, 5E5, 1, 2.00 \( \pm \) 0.02) | \( -3.71 \pm 0.01 \) | 57% |
| \( m_{1/3} = 13.3 \) Blackbody Models | | |
| (2000, 1.13 \( \pm \) 0.01) | \( -3.71 \pm 0.01 \) | 53% |
| (2100, 1.02 \( \pm \) 0.01) | \( -3.71 \pm 0.01 \) | 53% |
| (2200, 0.95 \( \pm \) 0.01) | \( -3.70 \pm 0.01 \) | 53% |
| \( m_{1/3} = 13.1 \) Synthetic Atmosphere Models | | |
| (1900, 5.5, 1E5, 0.25, 1.19 \( \pm \) 0.02) | \( -3.74 \pm 0.01 \) | 61% |
| \( m_{1/3} = 13.1 \) Blackbody Models | | |
| (1900, 1.26 \( \pm \) 0.01) | \( -3.69 \pm 0.01 \) | 54% |
| (2000, 1.13 \( \pm \) 0.01) | \( -3.69 \pm 0.01 \) | 54% |
| (2100, 1.04 \( \pm \) 0.01) | \( -3.69 \pm 0.01 \) | 54% |

Notes.

\(^a\) Synthetic atmosphere models are represented by \( (T_{eff}, \log(g), \text{cloud-top pressure}, \text{grain size}, \text{and radius}) \).

\(^b\) The fraction of the bolometric luminosity represented by the portion of the SED with measured constraints.

Our estimate of \( L_{bol} \) is \( \log_{10}(\frac{L}{L_\odot}) = -3.69 \) to \(-3.78\), consistent with the value reported by Bonnefoy et al. (2014).

We take a very conservative approach in comparing to the evolutionary model. We do not interpolate the evolutionary model between mass bins. Rather, in Table 5 we report the range of values for each predicted parameter for the mass bins whose luminosities bracket the luminosity range of \( \kappa \) And b.

We conclude that the \( T_{eff} = 1500 \) K models in Figure 4 are well outside expectations for an object with the luminosity of \( \kappa \) And b and are inconsistent with the predictions of evolutionary models. Table 5 shows a \( T_{eff} = 1564 \) K prediction for an age of 40 Myr, but this is due to the coarseness of the evolutionary model grid. The luminosity corresponding to \( T_{eff} = 1564 \) K is \( \log_{10}(\frac{L}{L_\odot}) = -3.99\), well below what we measure.

For the atmosphere fits to the \( m_{1/3} = 13.3 \) case, two 1900 K models are allowed within the 95% confidence interval, one...
with log($g$) = 4.5 and one with log($g$) = 5.0. The log($g$) = 4.5 model is consistent with the evolutionary model ranges listed in Table 5. Agreement between well-fit model atmosphere parameters and evolutionary model predictions is not a given, and in this case such agreement depends on specific cloud properties, including a very low cloud-top pressure (10^5 dyne cm^-2) and small median grain size (0.25 μm). While our atmosphere model fits match the evolutionary model predictions for both $T_{\text{eff}}$ and log($g$), the predicted radius is larger than that inferred with an atmospheric model fit. This suggests that a lower $T_{\text{eff}}$ model, which would require a larger scaling (radius) to intersect the data, may be more appropriate. Both temperature and median grain size both effect the model atmospheres in a similar way, imposing a global tilt across the 0.9–5 μm wavelength range. Consequently, finding a larger radius lower-temperature model may require further tuning the cloud parameters.

For the case with $m_{L'} = 13.1$ we find only one model atmosphere within the 95% confidence interval. In the top panel of Figure 5, we show this model and compare to the best-fit models from Bonnefoy et al. (2014) and Uyama et al. (2020). The 1700 K DRIFT-PHOENIX model identified by Uyama et al. (2020) provides a good overall fit and is consistent with the predictions of the evolutionary model. Our model provides a better overall fit to the data, especially providing a better match to the $L$-$M$ color of $\kappa$ And b. However, our best-fit model indicates a surface gravity of log($g$) = 5.5, inconsistent with the predictions of the evolutionary model.

We show a lower gravity fit to the data in the second panel from the top of Figure 5. This model is statistically ruled out by the fit because it underpredicts the $L$-band flux. This is the model that is allowed in the case of a fainter $L$-band flux discussed above. We note that lower gravity produces a bluer near-infrared to thermal-infrared color. This may seem counterintuitive given that low-gravity brown dwarfs are known to be red for their spectral type (see Faherty et al. 2016). However, effective temperature does not map to spectral type as readily for substellar objects as it does for stars. Both Stephens et al. (2009) and Filippazzo et al. (2015) show red low-gravity brown dwarfs are cooler than their higher gravity counterparts with the same spectral-type designation, and the discrepancy can be a few hundred Kelvin. So “low-gravity objects are red” is a statement that objects appear as earlier type for a given $T_{\text{eff}}$, rather than as extra red at fixed $T_{\text{eff}}$.

Since the low-gravity model is too blue, a cooler atmosphere may provide a better fit. We show in the third panel from the top of Figure 5 an 1800 K model that appears to get the gross colors of the SED correct. This model is statistically ruled out because of the residuals at the peak of the $K$ band.

The peak of the $K$-band is particularly sensitive to the pressure of the photosphere due to the significant opacity within the band from collisionally induced absorption of molecular hydrogen. High surface gravity is one way to affect a high-pressure photosphere, another is to remove metals from the atmosphere, making it more transparent and facilitating a view to deeper, higher pressure levels. In the bottom panel of Figure 5 we show an 1800 K, log($g$) = 4.5 model with subsolar metallicity. This model provides a very good fit to the data and provides a radius consistent with evolutionary models. Formally, with a $\Delta \chi^2 = 30$ from the best-fit model, the subsolar metallicity model is ruled out at the 4σ level (six degrees of freedom). Remaining issues could likely be resolved with minor modifications to the atmospheric parameters, but a detailed focused fit is beyond the scope of this paper and is unwarranted given the level of systematic errors present in the data set.

Given the young age of the $\kappa$ And system it is unlikely to be significantly metal-poor. We looked up the members of the Columba association listed in Bell et al. (2015) in the Hypatia Catalog Database of stellar abundances (Hinkel et al. 2014). We found four matches covering spectral types spanning F3 to M0 with metallicity, this is likely a signature of the formation process, and could be an important clue to better understand the physical mechanism that produced the low-mass companion.

In both the $m_{L'} = 13.3$ and the $m_{L'} = 13.1$ cases, good alignment with the data requires specific cloud properties, namely a low cloud-top pressure and small median grain sizes. This is a robust result, not affected by choosing between the two $L'$ photometric scalings. We note that the DRIFT-PHOENIX model shown in Figure 5 also includes a small average grain size in the upper layers of the atmosphere (Witte et al. 2009, 2011).

### 6. Conclusion

We present the first high-contrast $L$-band spectrum from LBTI/ALES. The spectrum of $\kappa$ And b—a young low-mass companion with a mass ratio $\lesssim 0.7$% with respect to its B9 host star—is used to constrain atmosphere models. Our ALES observation is about 20% fainter over the $L'$ band compared to previously published photometric measurements. A 2013 LBTI/LMIRCam observation of $\kappa$ And at $L'$ yields a flux consistent with the ALES value. We combine ALES data with spectra covering the $Y$ to $K$ bands and with $M'$ photometry, yielding measurements of the substellar companion SED spanning 0.9 to 4.8 μm. Using the ALES $L$-band flux scaling, the data are well fit by an L3-type brown dwarf from the field. If previous photometry is more accurate, then none of the template brown dwarf spectra we compare to can match the red near-infrared to thermal-infrared color. The data precisely constrain the bolometric luminosity of the object, which we use as input to evolutionary models. We find atmospheric models consistent with the predictions of evolutionary models for atmospheres with $T_{\text{eff}} = 1800$–1900 K and log($g$) = 4.5–5. Clouds composed of small grains extending to high altitudes are required by the data whether the ALES $L$-band flux scaling is used or not. There is a hint of substellar metallicity in the
The case of the brighter $L$-band flux scaling. Future observations improving the $L'$-band photometry of both $\kappa$ and $A$ and $b$ will help clarify if subsolar metallicity is required. Improved atmospheric constraints will also be facilitated by independent verification of the shape of the $K$-band emission and improved precision of the $M'$ photometry.

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