Biases in Modeling Thermal Emission Spectra for Hot Jupiters and Implications for Directly-Imaged Exoplanets

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Introduction

The study of exoplanet atmospheres has evolved over time from early 1-dimensional (1D) radiative transfer models to incredibly complex and computationally intensive general circulation models (GCMs). Along with advances in telescopes and observational techniques, this evolution has allowed for sophisticated inferences about the structure and composition of exoplanet atmospheres.

Both forward and retrieval models in 1D remain popular because of their simplicity which directly translates to less computational requirements and faster modeling. 1D models generally are used over 3D models in cases of fitting model data for this reason.

However, studies have shown detectable, explicitly 3D effects due to e.g. day-night temperature gradients (Caldas et al., 2019), chemical species distribution (Pluriel et al. 2020, Wardineir et al., 2023), and clouds (Gilbert-Janizek et al., 2024) . We show that this problem exists in modeling emission spectra as well and extrapolate the effect this phenomenon could have on direct imaging studies.

Modeled Thermal Emission Spectra Can Have a Spatial Bias

We find noticeable differences in the simulated emission spectrum for a GCM model of HD189733b when a 1D spatially averaged p-t profile is used as opposed to the full 3D output.

We use the SPARC/MITgcm (Showman et al., 2009) to model the atmosphere of the canonical hot Jupiter HD189733b assuming an atmospheric metallicity of 1x Solar and 5x Solar. Using these GCMs, we use PICASO (Batalha et al. 2019) to produce spectra from the 1D spatial averages of the planet's dayside (Fig 1, dashed lines, Kataria et al. 2016) and from the dayside 3D grid (solid lines). The spectra are then convolved to the MIRI/LRS bandpass for comparison with *JWST* observations.

For 3D inputs, PICASO integrates over the "visible" grid cells using a Chebyshev-Gauss method (Horak & Little, 1965), i.e. each grid cell is weighted according to the angle between normal from the cell and the observer and then summed (Fig 3). When the 1D averages are used, PICASO simulates a 3D model by placing the 1D profile at every grid point then using the same method to integrate.

As seen in Figure 1, the 1x solar spectra show good agreement between 1D and 3D, but the spectrum of the 3D 5X solar model has an overall higher total flux than the 1D averaged spectrum. Because of the larger temperature gradient across the dayside, the center grid cells of the 5x solar metallicity model are significantly hotter than the dayside average. As these grid cells are more highly weighted in the Chebyshev-Gauss integration, the total simulated flux also becomes noticeably larger when the summation of the flux is implemented (Fig 2).

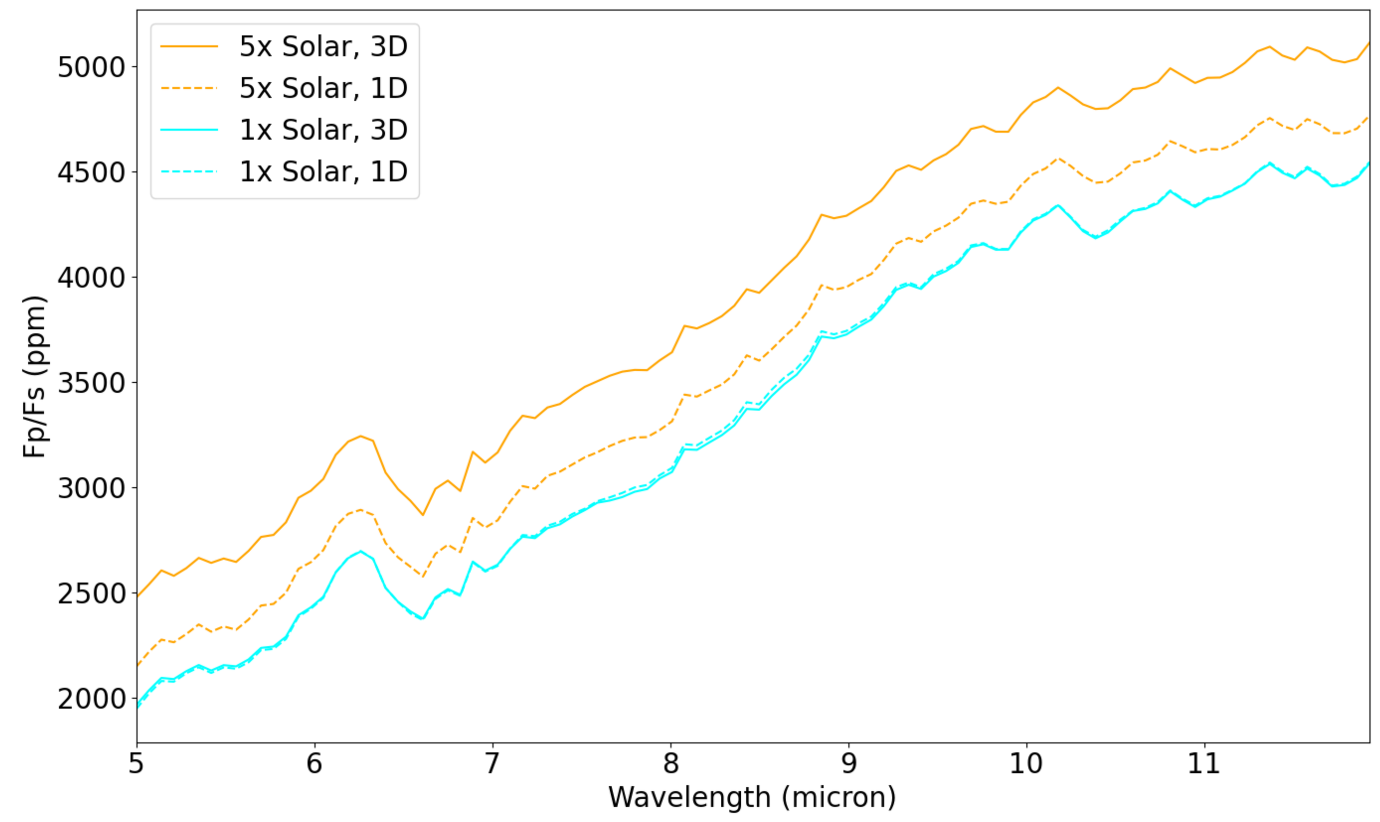

Figure 1. Simulated spectra from the results of the SPARC/MITgcm simulations of HD189733b assuming 1x (cyan) and 5x (orange) solar metallicity. These spectra were created using PICASO with the full 3D dayside (solid lines) and inputting a 1D dayside average P-T profile (dashed lines). Afterward, the simulated spectra were convolved with the MIRI/LRS bandpass for comparison with *JWST* data.

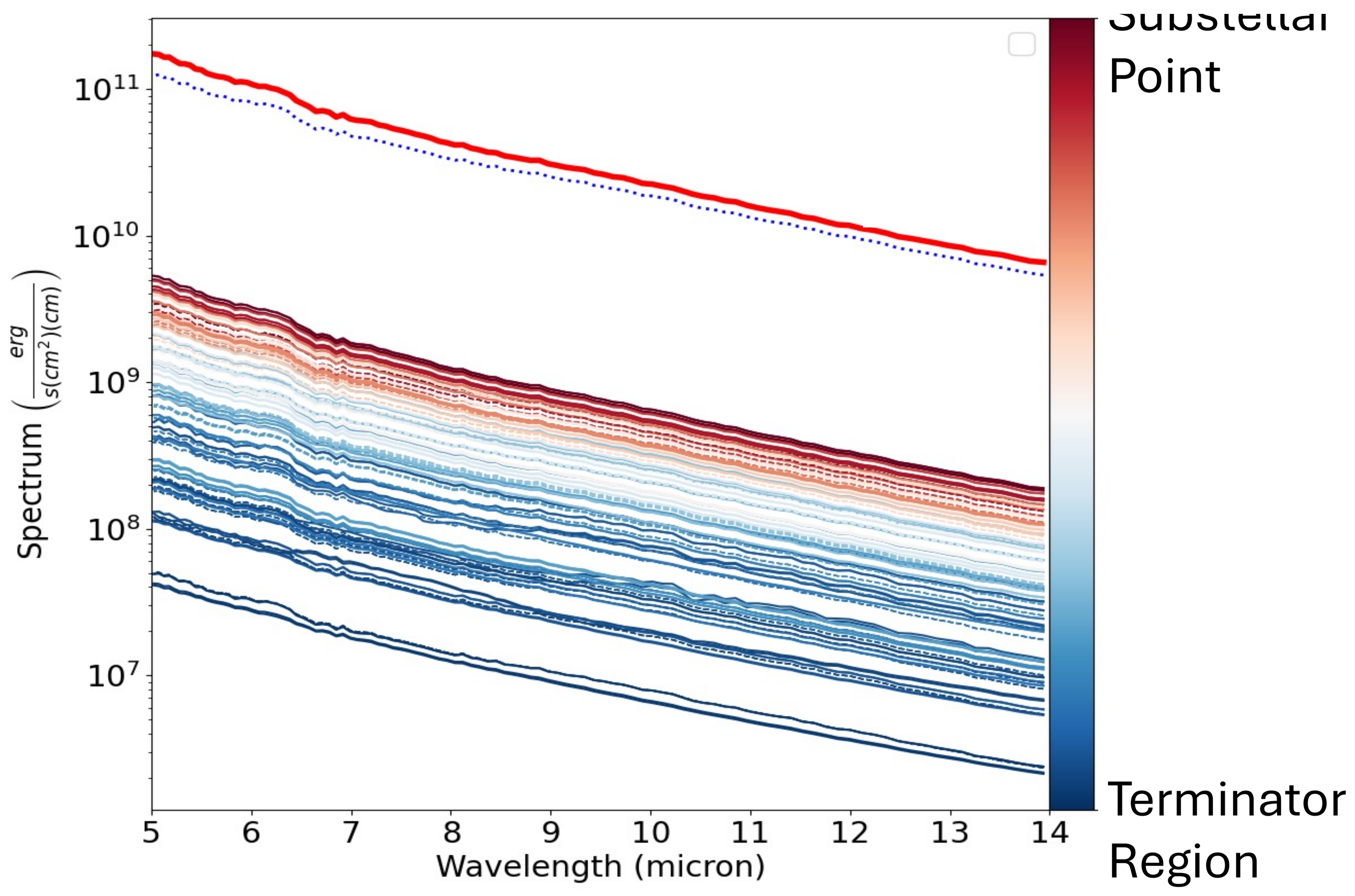

Figure 2. Each curve shows the simulated spectral flux at the top of the atmosphere for each point in the PICASO grid in the 5x Solar models. The solid lines correspond to the spectra created from the 3D input, while dashed lines correspond to the spectra created from the 1D dayside average input. Curves colors correspond to their position on the grid: red lines are close to the substellar point and blue lines are near the terminators. Also plotted are the summed spectra, clearly showing the difference between using 3D inputs (red, solid) and using the 1D average (blue, dashed).

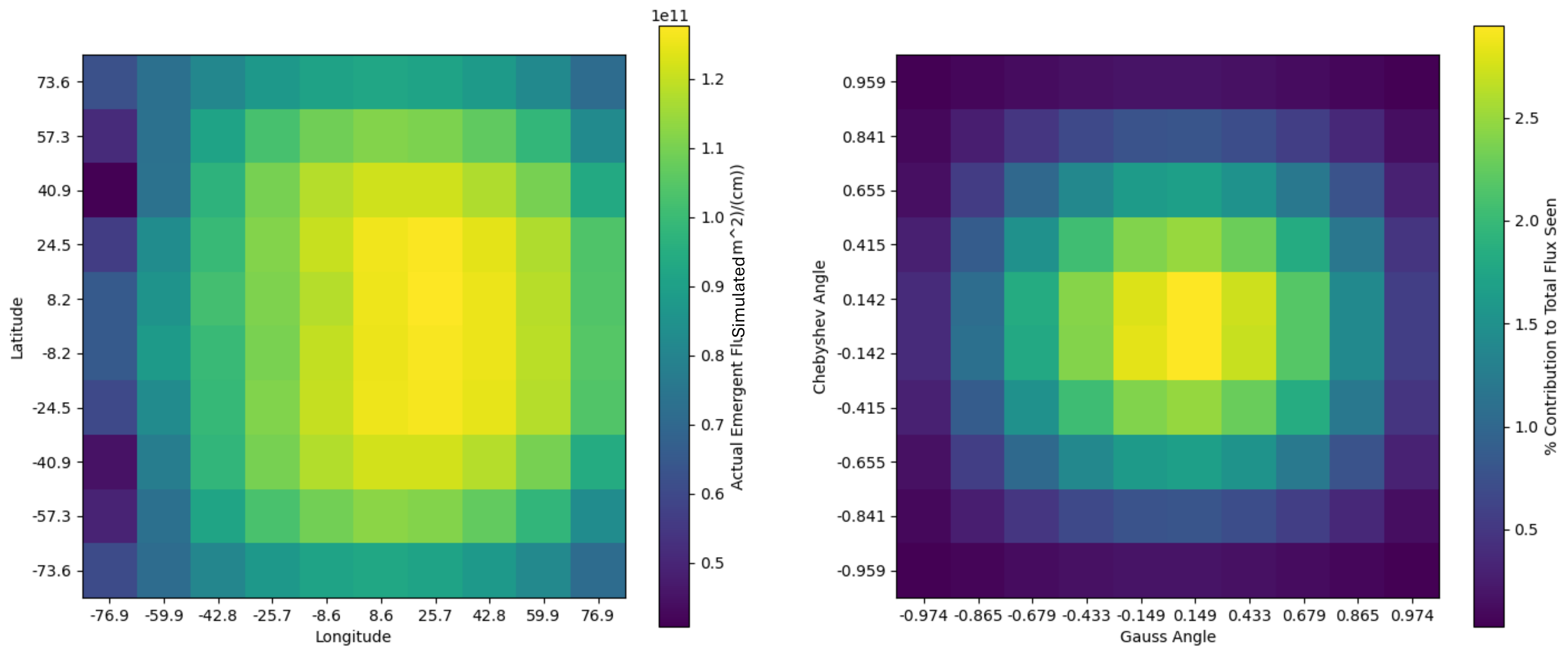

Figure 3. PICASO grid for the 5x Solar model showing the simulated flux at the top of the atmosphere with 3D inputs (left) and the same grid with the Chebyshev-Gauss weights applied (right). This figure illustrates how a grid cell's latitude and longitude impact its contribution to the total flux. The grid cells nearer the center (the substellar point in this case) are weighted higher than those at the edges (the terminators in this case). As the hottest and therefore most emissive parts of the model are near the center, they have an outsized effect on the total flux.

Reflection Spectroscopy Could Have a Similar Bias

As with thermal emission, if an area with higher-than-average emergent flux is near the center of the face of the planet facing the observer, that area will contribute more to the total observed flux than other areas near the edges of the observable disk as the center has more apparent area to an observer. As albedo in general is dependent on the angle of incoming light, the orientation of the object plays a large role in the signal received.

Spatially averaging over a reflecting atmosphere/surface with high albedo contrast from the center to the edge of the observed disk can therefore under- or overestimate the expected flux, leading to errors in interpretation.

These phenomena may be below the detection threshold of current telescopes but must be considered before the launch of telescopes capable of more precise observations such as *Roman Space Telescope* or the *Habitable Worlds Observatory*.

Challenges and Next Steps With 3D Modeling

On-the-fly chemical and cloud microphysical modeling is computationally expensive, but necessary for 3D retrievals and eliminating spatial bias entirely. Unfortunately, due to the high computational demand of self-consistent chemical and cloud models, 3D GCMs are not able to be easily used for retrievals. Some efficient solutions have been created for 3D retrievals with transmission spectroscopy (e.g. MacDonald & Lewis, 2022) and inventive use of higher resolution, more flexible 1D retrieval models has been used to approximate 3D thermal structure when enough data points can be provided (Blecic et al., 2017).

Machine learning has the potential to assist the speed of 3D modeling, but the methods have challenges to overcome. Physics informed machine learning models show promise in effectively simulating fluid flow and other physics (e.g. Karniadakis et al., 2021), but attempts to use them to implement cloud physics have up to 30% errors compared to self-consistent implementations (Meyer et al., 2022). Before such models are rigorously tested and benchmarked against current self-consistent GCMs, machine learning has the potential to accelerate steady-state convergence by extrapolating the spin-up phase of modeling and could help in modeling chemistry and microphysical processes.