Draft version June 17, 2018
Preprint typeset using LaTeX style emulateapj v. 12/16/11

CHARACTERIZING ATMOSPHERES & SURFACES OF TERRESTRIAL EXOPLANETS
ASTROPHYSICS 9A: INTRODUCTION TO RESEARCH IN ASTROPHYSICS

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ABSTRACT

Preparing for the launch of the WFIRST space telescope, we present a technique to characterize exoplanet surfaces features and their atmospheres. Using the optical wavelength spectrum, we can compare spectra to one another by utilizing the chi-squared statistical measure, directly analyzing the difference between each data point. While not many real observations have been made of terrestrial exoplanets, using our current models and simulated observations, we can use this overall method to correctly identify and characterize our simulaitons. We are prepared for the launch of WFIRST in the optical spectrum, however, we must account for every variable, like noise and chemical composition, and can always improve our models and simulated observations.

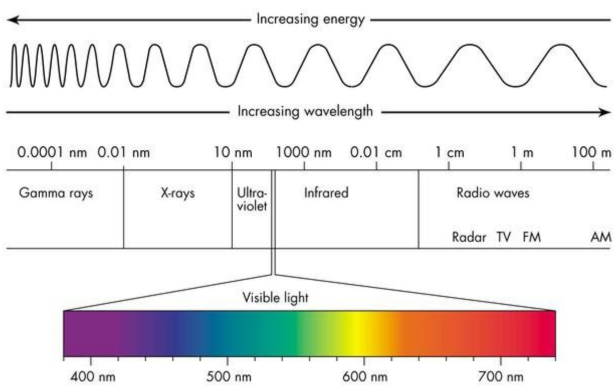


Fig. 1.— The visible light and full electromagnetic spectrum

1. INTRODUCTION

The word exoplanet has been thrown around often, especially with the data coming from the Kepler spacecraft. An exoplanet is simply a planet that orbits a star that is outside our solar system. The spectra we measure on these planets shows the absorption or emission of light as it passes through the atmosphere. We focused on emission spectra of terrestrial exoplanets, where light from a star passes through the atmosphere, reflects off the surface, and passes back towards us, going through the atmosphere again. Sensitive instruments like spectrometers and photometers graph the normalized flux, or the amount of light, with the wavelength. The emission spectra can vary greatly in the presence of clouds, oceans, or forests, as each color that is reflected has a different wavelength. In Fig. 1 we see visible light and each colors corresponding wavelengths. Knowing these wavelengths of visible light, we can identify the surface features.

We already have observations from the Extremely Large Telescope (ELT), made by the European Southern Observatory (ESO), that gives us with insight to the atmospheric compositions of thousands of exoplanets. The James Webb Space Telescope (JWST) will hopefully launch within the next two or three years as well, providing us with data for the next decade and beyond. The hardest part about analyzing these exoplanets is waiting for their transit, or when they pass in front of the host star. This is how the light passes through the atmosphere and into our instruments. Depending on the period of orbit, it may take a while to take a full observation.

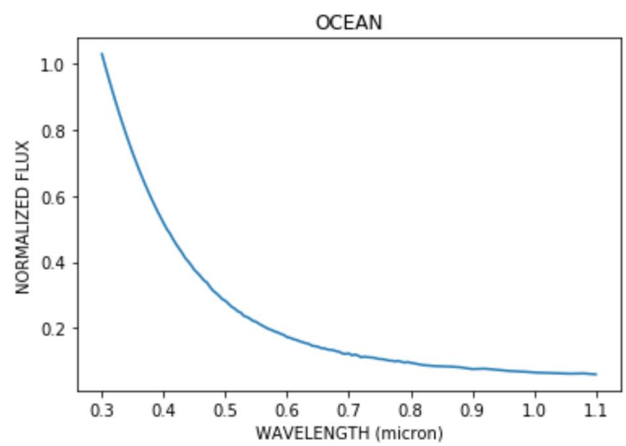


Fig. 2.— Ocean spectrum

Spectra like Fig. 2 and Fig. 3 are perfect, pre-made, and contain no noise, only showing the relationship between wavelength and the normalized flux that is observed. We can take these theoretical models and compare them with data we have taken on our own solar system.

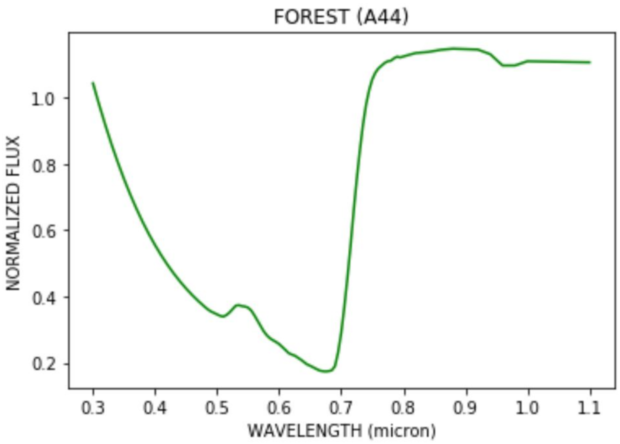


FIG. 3.— Forest spectrum

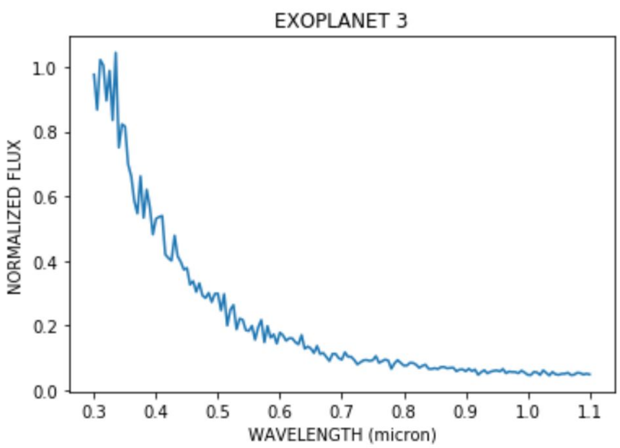


FIG. 4.— Exoplanet spectrum

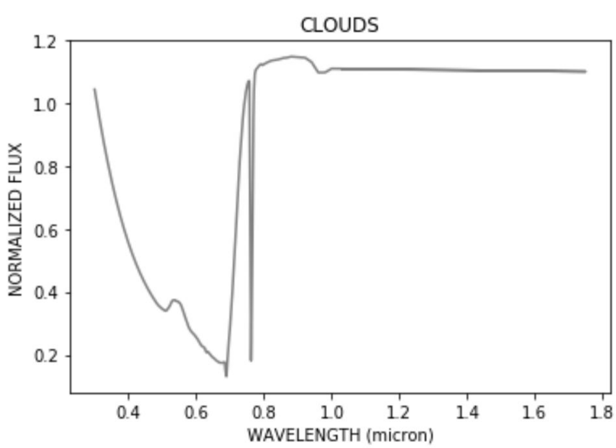
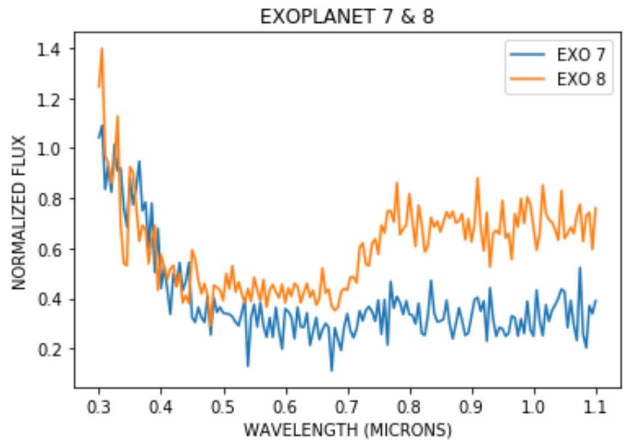


FIG. 5.— Cloudy spectrum

The differences between two spectra can be shown statistically or also graphically, as the ocean spectrum in Fig. 2 matches the shape of the exoplanet curve in Fig. 4. The comparison of Fig. 3 and Fig. 4 is an example of two graphs that do not match.

Keeping this measurement in mind, we can analyze more realistic spectra. A combination of different environments, like oceans and forests on Earth, provides a



spectrum that is harder to identify. Noise and complex weather patterns also plays a big factor, distorting observations. Fig. 5 shows the effect that clouds have on the emission spectra.

While these previous examples had nice, smooth curves, the spectra we analyzed were pre-made graphs that have little to no noise and strong, obvious characteristics. However, the knowledge we gain from studying these basic spectra allows us to apply this information to more realistic data sets in the future. In this paper, we are looking at more advanced spectra, deducing their compositions, analyzing the effect of noise, and weighing the possibility of life.

2. METHODS

In our group, we divided into two groups: observers and theorists. I focused on writing code in Python that compares combinations of spectra to unknown exoplanets, while Demetrio cataloged future technologies and all of the nearby stars within ten parsecs.

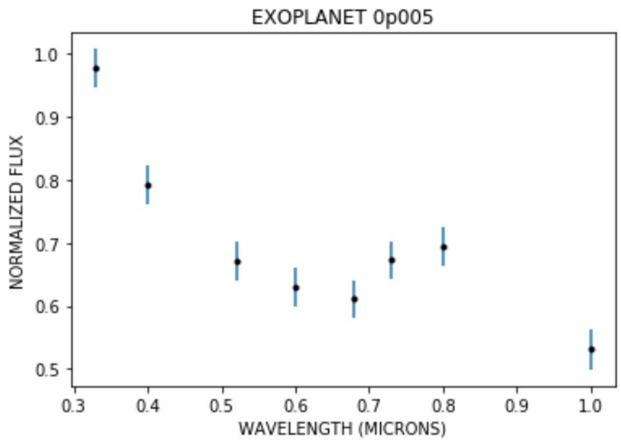
2.1. *Chi-squared Calculations*

Exoplanets come with a variety of environments. Because of this, one perfect spectra cannot be used to compare to an unknown exoplanet, as that spectra might have a combination of ecosystems on its surface. To create these combinations, we used multiple 'for' loops to grab percentages of each of the spectra. And because we did not know how many spectra were used, we had to run through two, three, four, five, and six combinations of the six total spectra.

The new combination spectra can then be compared to the unknown exoplanet that we are trying to characterize. We can quantify this using the chi-squared statistic, where each of the data points are compared to one another to analyze the difference between them, given by:

$$\chi^2 = \Sigma(\frac{Observed - Expected}{Expected})^2 \quad (1)$$

In Python, the scipy.stats package allows us to input two similar lists and it will return the chi-value. Each combination will have 10^x chi-values, where 'x' is the number of spectra used in the combination. By putting all of the values into a multi-dimensional array, we can use the numpy package to find the minimum value for a given combination. The lowest value is then determined



to be the correct combination model for the respective exoplanet.

While the first couple unknown exoplanet spectra we are looking at have full, complete observations, we cannot receive flux values across the whole visible wavelength spectrum in the real world, or we only have a very small amount of light to work with. In this case, we have to take light values within a certain band and average them. This results in a singular data point at a specific wavelength. To be able to do a chi-squared operation on this type of spectrum, we must take the average of both spectra and compare those two values.

To find the average of the spotted spectrum, we took normal, Gaussian distributions centered around the particular wavelengths and multiplied them by the combination spectra. Because the data points are an average from a certain band width, multiplying the Gaussian allows us to find the average of the combination spectra over a given area, as the Gaussian represents an average that weights the values within one standard deviation of the wavelength more than the edges. We can then use the same chi-squared technique to compare the combination and spotted, unknown spectra together.

We could not take the integral of the entire combination spectra and compare it to the estimated averages of the spotted spectra, because the integral of the combination spectra did not account for shifts in different regions of the graph. For example, two different looking spectra could have the same area under the curve. A graph with low flux in the shorter wavelengths and higher flux in the longer wavelengths would be calculated to have the same area under the curve for a graph with high flux in the shorter wavelengths and lower flux in the lower wavelengths. The individual regions of the graph must be compared to the corresponding regions of the combination spectra, as the combinations show certain features in certain regions, therefore the total flux cannot be used.

2.2. *Cataloging Stars*

There are hundreds of thousands of stars and exoplanets in the universe, so sorting helps them become more manageable. Demetrio made a catalog of all of the stars within ten parsecs. This is the distance to a star, such that its apparent change in location in the sky is one arc second. As the Earth revolves around the Sun, the physical location of stars do not change, but our viewing angle of them does as we move from one side of the Sun to the other. This is called the paralax and the paralax

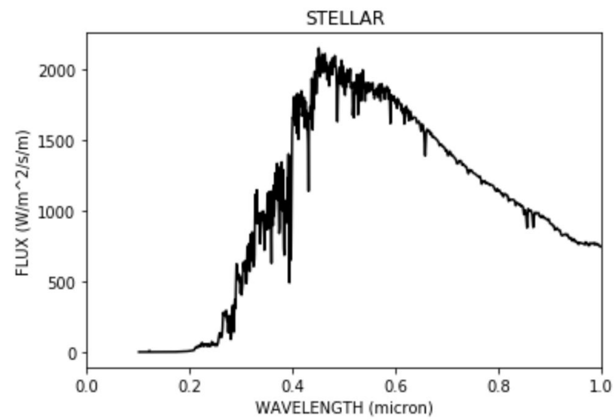


Fig. 6.— Stellar spectrum

angle for one parsec is equal to one arc second.

By downloading a database and importing it into Python, and combing through the data, Demetrio can sort by certain characteristics. For example, the database has different categories for the type of star, like M-type and K-type, as well as other physical properties like declination.

3. RESULTS

With our two groups, the theorists and the observer, we each were tasked with different jobs, with the overall goal of characterizing exoplanet atmospheres and finding potentially habitable exoplanets.

3.1. *Observer*

Demetrio found a telescope that was able to observe the wavelengths that our model spectra used. In this case, our models were looking in the visible wavelength spectrum, from around 0.3 microns to around 1.0 microns. Using the minimum flux requirement for the WFIRST telescope and the flux values that were reflected off the planet from the star, he determined that we would be able to see Proxima Centauri B, an exoplanet orbiting around the star Proxima Centauri. This exoplanet is within ten parsecs, thus giving more accurate, higher resolution spectra. Then, he gave simulated observations to the theorists to characterize.

3.2. *Theorist*

The observations used a Gaussian distribution to average the data within a certain wavelength bin. This normal distribution gave more preference to photons around the center wavelength than the photons in the higher or lower wavelengths, relative to the center point. However, rather than simply combining different models together and running them across a Gaussian distribution, this time, the flux from the star (Fig. 6) and a geometric ratio had to be taken into account. The equation for the observations is given by:

$$OBS = MODEL \times STAR \times (\frac{r^2}{4d^2}) \quad (2)$$

This equation uses the radius of the exoplanet and distance to the planet in parsecs (or equivalent units), representing the ratio of photons that hit the exoplanet relative to the total coming off the star. The spectrum from

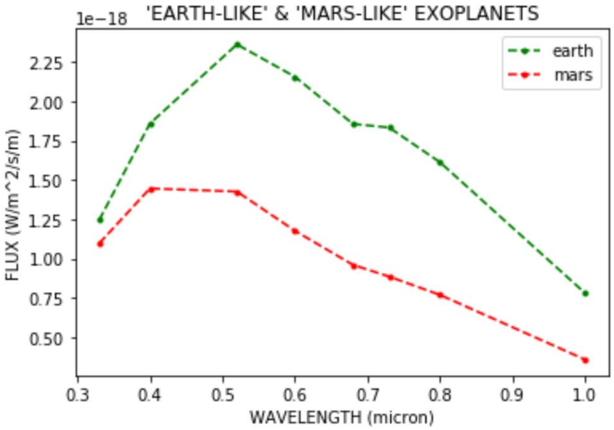


Fig. 7.— 'Earth-like' and 'Mars-like' exoplanets

the star is often higher resolution and contains many more data points than our model, so we had to interpolate this larger data set down to a smaller data set to match the size our models.

The right side of this equation is then run through a Gaussian distribution centered at each of the wavelengths. The sum of the Gaussian multiplied by the right side of the equation gave an overall, normalized flux value, which could then be compared using the chi-squared technique with the flux values in the observations.

We used this to determine the surface features of an Earth-like planet and a Mars-like planet four parsecs away (Fig. 7). For the Earth-like planet, the combination of 10 percent sand, 80 percent ocean, and 10 percent forest with intermediate clouds produced the lowest chi-squared value. With the Mars-like planet, 100 percent of the surface could be characterized with sand.

With this information, in theory, we should be able to characterize exoplanet surfaces when we take real observations. However, the real-world observations include more noise and extra variables than we considered in this project. Ever aspect of these planets and our instrumentation must be taken into account to accurately and confidently characterize exoplanets and their atmospheres.