BAYESIAN ANALYSIS OF JUNO/JIRAM’S NIR OBSERVATIONS OF EUROPA. Ishan Mishra\textsuperscript{1,2}, Nikole Lewis\textsuperscript{1,2} and Jonathan Lunine\textsuperscript{1,2}, \textsuperscript{1}Department of Astronomy, Cornell University, \textsuperscript{2}Carl Sagan Institute (correspondence email: im356@cornell.edu).

Introduction: In this work we have analyzed high-quality near-IR (2-5 microns) reflectance spectra of Europa, collected by the JIRAM instrument on Juno [1]. We carry out a fitting exercise with the Hapke bi-directional reflectance model, in a Bayesian inference framework. The advantage of using a Bayesian inference framework is that 1) it allows exploration of a huge parameter space, for non-unique solutions and obtain uncertainties on the derived best-fit parameters 2) it is robust to low-SNR data when it comes to constraining the parameters, as can be demonstrated through analysis on simulated data 3) Bayesian model comparison provides a mechanism to quantify the detection significance of the different components we put into our model (e.g. amorphous ice, crystalline ice, etc.).

Data: Juno/JIRAM obtained 419 high quality spectra of Europa (see Table-1 of [1]). In this analysis, we select 4 spectra with constrained observing geometries, taken during observation session JM0051_170901_105708 (orbit number 8), to exercise our Bayesian retrieval framework. We obtained the normalized spectra from the authors of [1] through personal communication and proceeded to ‘clean’ them (remove NANS, outliers, etc.). We calculated the error on the spectra using the noise equivalent spectral radiance or NESR (also obtained from authors of [1]). Since all the 4 spectra have the same observation geometry (corresponding to the same pixel on Europa), and to simplify the analysis, we use the mean spectrum. (Fig. 2)

Hapke Model: As proposed by Hapke ([2],[3]), in the geometric optics regime, the bidirectional reflectance (or radiance factor $I/F$) of a surface that consists of particles of arbitrary shape in close proximity to one another is given to a good approximation by:

$$I/F(\mu, \mu_0, \omega) \approx K \frac{\omega}{4(\mu + \mu_0)} P(\omega + \mu/K) H(\omega, \mu_0/K) - 1$$

Here $I/F$ is the radiance factor, which is the ratio of bi-directional reflectance of a surface to that of a perfectly diffuse surface (Lambertian) illuminated and observed at $\theta=0$, $\mu$ is the cosine of the emission angle, $\mu_0$ is the cosine of incidence angle, $\omega$ is the phase angle, $K$ is the porosity coefficient, $P$ is the particle phase function and $H$ is the Ambartsumian-Chandrasekhar function that accounts for multiple scattered light. Since the phase angle of all of Juno’s observations is ~ 90 deg., due to its polar orbit, we have ignored functions that account for backscattering and other effects which become important at low phase angles. For intimate mixtures, the Hapke equation can be used by first taking a weighted mean of the single scattering albedos of all the components. For a given component, its weight is a product of the cross-sectional area of the average spherical grain and its particle number density. In this preliminary work, we focus on two components: amorphous and crystalline water ice (optical constants at 120 K from [4]).

Bayesian inference and model comparison: Informed by a set of observations $y_{\text{obs}}$ (the $I/F$ spectrum in our case), we can calculate distributions of model parameters $\theta$ with Bayes’ theorem:

$$p(\theta | y_{\text{obs}}, M) = \frac{p(y_{\text{obs}} | \theta, M) p(\theta | M)}{\int p(y_{\text{obs}} | \theta, M) p(\theta | M) d\theta} = \frac{L(y_{\text{obs}} | \theta, M) \pi(\theta | M)}{Z(y_{\text{obs}} | M)}$$

where $L$ is the likelihood function, $\pi$ is the prior and $Z$ is the Bayesian evidence. $p(\theta | y_{\text{obs}}, M)$ is the posterior function, which gives us the distribution of the different model parameters in the parameter vector $\theta$. Since we assume gaussian errors on the data, the likelihood function is gaussian and is proportional to $\exp(-(y_{\text{obs}} - y_{\text{mode}})^2)$. Hence, a better fitting model has a higher likelihood value. For priors, we assume uniform distribution, which is a good practice so as to not bias the posterior function. The Bayesian evidence $Z$ is a very useful metric to compare models in light of the data, where a higher value of $Z$ indicates a better fitting model. The Bayesian evidence is the integral of the product of the likelihood function $L$ and prior function $\pi$, over the entire parameter space. Model comparison with Bayesian evidence, along with Bayesian parameter inference, has been extensively used in other areas of astronomy like exoplanet science and cosmology, but hasn’t been applied to solar system spectroscopy studies.

Early Results: The free parameters of our two-component model are 1) grain diameter of amorphous ice 2) grain diameter of crystalline ice 3) particle/grain number density fraction (or ‘abundance’) of amorphous ice. As stated before, for all three parameters, we consider a uniform prior function on an interval that insures their physical relevance (10-1000 microns, 10-1000 microns, and 0-1 respectively). We
explore this parameter space with MCMC and Nested Sampling algorithms [5] (the latter allows easier calculation of the Bayesian evidence integral). The results from this exercise can be summarized as follows:

1. The retrieval over the entire 3-d parameter space, as defined above, shows bimodal distributions for the grain sizes and abundances, indicating a solution with one large and one small grain size population.

2. To check our intuition, we explored all combinations of amorphous and crystalline ice populations (e.g. only amorphous, only crystalline, small amorphous + large crystalline, etc.). The model with the highest Bayesian evidence consists of two populations of amorphous ice grains: around 6% (of mass per unit volume) of small ~20 microns grains and 94% of ~600 microns grains (Fig. 1).

3. The maximum likelihood (ML) solution of the small and large amorphous ice model (as well as the ML solutions of other models) is not able to fit the data at around 2.6 and 3.5 microns, which might indicate the presence of non-ice components that strongly absorb in these wavelength regions. (Fig 2).

**Ongoing and Future work:** In the next phase of this project, we have incorporated non-water ice components in the mixture, and there have been numerous species proposed to exist on Europa’s surface[6, 7, 8]. We have obtained NIR optical constants, at the appropriate temperatures of ~ 100K, of sulfuric acid octahydrate (personal communication with Rob. Carlson [9]) and CO₂ & SO₂ ice [10]. Most of the major non-ice species that have been proposed to exist on Europa (hydrated salts, hydrated sulfuric acid, etc.) don’t have cryogenic NIR optical constants available publically. Our work, like previous analyses of Europan data, highlights the need for laboratory measurements of optical constants in the 2-5 microns wavelength regime. Equipped with a rich database of NIR optical constants, we can employ advanced techniques like Bayesian inference and machine learning to study the wealth of Europan data that already exists [1,6,7,11,12,13] and build a comprehensive picture of Europa’s surface. This groundwork will allow us to consider the robustness with which we will be able to detect, and constraint, other minor species of interest like organics, in preparation of upcoming missions like Europa Clipper and JUICE.


**Figure 1.** The ‘corner’ plot generated from samples of Bayesian retrieval using the model that had two populations of amorphous ice: a large population (prior range: 100-1000 microns) and a small grain size population (prior range: 10-100 microns). The diagonal parameter distributions are of the common logarithm of population-1 grain size (in microns), the common logarithm of population-2 grain size (in microns) and the grain number density fraction of population-1 respectively, from top to bottom. The other three plots are pair-wise 2d distributions, that illustrate the correlations between parameters.

**Figure 2.** The JIRAM data along with the maximum likelihood solution for the model with two amorphous ice populations (as in Figure 1). Here D_am1 indicates grain diameter in microns of population-1, mf_am1 indicates the mass fraction per unit volume of population-1, and so on.