Analysis of Variations in the Io Plasma Torus
Using Galileo PLS data

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1. INTRODUCTION

Most people are aware that Earth has a magnetic field that causes a compass needle to orient itself toward the poles. However, beyond this context, many do not give the existence of this field a second thought. After all, it does not seem to have any direct effects on daily life. Yet, in ways researchers are only beginning to understand, Earth’s magnetic field appears to play a crucial role in mediating the variable conditions of the space environment, known as space weather. Just as ordinary weather can turn violent and cause extensive damage, severe space weather events have already cost some companies hundreds of millions of dollars in damage [Fletcher, 2003]. Without a magnetic field surrounding the planet in a protective bubble, called a magnetosphere, space weather would not allow life to exist on Earth in the first place. First, I will review the significance of magnetospheres, and what has been done to better understand them. I will then focus on the primary topic of this thesis: learning about the Jovian magnetosphere through data analysis of Galileo PLS instrument observations.

1.1 What is a magnetosphere?

According to David Stern [1989], study of the Earth’s magnetic field began with the invention of the magnetic compass in China around 1000 A.D. Over the next several centuries, observers found the field configuration of the Earth to be basically dipolar (i.e., like that of a bar magnet), and although it seemed to be mostly constant over time, it would occasionally get disturbed for a day or so. Some disturbances were observed in vastly different parts of the world at the same time, which implied that they were occurring on a global scale. It was not apparent what mechanism could affect such large
regions of space until astronomers realized a correlation between magnetic disturbances and the number of sunspots on the Sun.

Although this correlation was not direct, Stern claims that it was enough to motivate Norwegian scientist Kristian Birkeland to conduct experiments concerning moving charged particles around a spherical dipole magnetic field. In 1896, Birkeland concluded that streams of electrons originating from the Sun could potentially be deflected towards the Earth’s magnetic poles, giving rise to magnetic disturbances and the aurora. Stern notes that the Sun has not been observed to emit electron beams toward Earth, but theorists like Sidney Chapman and Vincent Ferraro [1933] were able to extend Birkeland’s theory to allow interactions with clouds of both ions and electrons, collectively called plasma. Their model predicted that the Earth’s magnetic field should distort such that it would form a cavity of low-density plasma around the Earth, effectively isolating it from the incoming plasma stream. Such a situation was long thought to be rare and short-lived. However, a theory proposed by Eugene Parker [1958] that predicted that the Sun should be constantly emitting supersonic plasma in all directions. With the advent of the Space Age, satellite measurements confirmed Parker’s predictions. Therefore, this cavity is an ever-present entity shielding the Earth from constant bombardment of high-energy solar plasma, and it is now known as a “magnetosphere” [Stern, 1989].

1.2 **Why do we care?**

Even with some background on what a magnetosphere is, it may not be obvious why it deserves so much attention. After all, people would not even know it exists if they could not observe its effect on magnetically responsive objects like compass needles.
Nevertheless, life on Earth depends as much on the planet’s magnetosphere as it does on sunlight or water, especially as technology becomes increasingly electronic. All power grids comprise long wires with AC current constantly flowing through them, and this is only stable because the magnetosphere is able to shield out any external electric or magnetic fields from space weather. However, the magnetosphere is not infallible, and when a significantly violent space weather event is directed at Earth, the ‘bubble’ around Earth undulates and contorts significantly. According to the laws of electricity and magnetism, a changing magnetic field will induce an electric field, and this new electric field can create currents much larger than what existing power grids can handle. For example, on March 13, 1989, six million residents across the province of Quebec lost all electrical power for over nine hours because the Hydro-Quebec power system was rapidly overloaded as the result of an intense geomagnetic storm (as these disturbances have come to be known) [Boteler et al, 1998].

Fortunately, the effects of space weather are somewhat limited on the Earth’s surface because our thick atmosphere is another buffer between daily life and space weather—although it should be noted that the atmosphere would be stripped away without a magnetosphere to protect it [Vasyliūnas, 2011]. High above the atmosphere, nearly everything is either plasma or electromagnetic fields, and that creates an environment that is much more susceptible to changes in the magnetosphere. While this may not have been a serious problem 75 years ago, large companies and society as a whole have now become heavily invested in satellite technology, which is extremely vulnerable to space weather effects. On January 20, 1994, two of Canada’s Telesat communication satellites began to spin out of control due to electrostatic discharge (ESD)
within their gyroscopic circuits. These ESDs were the result of spacecraft charging, meaning that the satellites gained a high level of charge from unusually high levels of plasma bombarding them. The strong electric fields created by the charged spacecraft damaged the circuit elements permanently. The high plasma levels occurred due to a geomagnetic storm, and besides having to deal with a whole country of angry customers, Telesat incurred costs of $50- $70 million in order to repair the satellites [Bedingfield et al. 1996]. These high-cost problems, along with radio communications blackouts, radiation poisoning to astronauts and several other effects, will continue to threaten our technological progress unless we can gain an understanding the magnetosphere and how it responds to space weather.

1.3 **What’s been done to understand them?**

Prior to the satellite era, methods of measuring the Earth’s magnetic field were very limited and only a narrow range could actually be observed. Then, beginning with Sputnik 3 in 1958 [Olsen et al. 2010], measurements of the magnetic field have abounded, and the resolution of those measurements is constantly improving. There are currently several missions in orbit around the Earth investigating the physical conditions of the magnetosphere. The Van Allen Probes, launched in August of 2012, are studying the hostile environment within the Van Allen radiation belts, distinct regions of very-high-energy plasma encircling the Earth. The probes are investigating the possible sources of these belts, and they are collecting data on how they respond to geomagnetic activity. Another active area of magnetospheric research is a phenomenon known as “magnetic reconnection.” Normally, magnetic field lines exert enough intrinsic pressure to keep them distinguishable from other field lines. However, when external pressures are
sufficiently high to squeeze oppositely directed field lines together, the lines effectively
“reconnect” and release huge amounts of energy as they re-equilibrate. The Time History
or Events and Macroscale Interactions during Substorms (THEMIS) mission is composed
of five NASA satellites that have been orbiting since 2007. THEMIS has already
confirmed an electromagnetic connection between the Earth and Sun via Birkeland, or
“field-aligned,” currents, and it was the first mission to directly prove that magnetic
reconnection is the triggering mechanism behind geomagnetic storms. To follow up on
these observations, the Magnetospheric Multiscale Mission (MMS) will use four
satellites flying in a constant spatial configuration to probe the physics of magnetic
reconnection on the microscopic scale [Olsen et al. 2010]. All of these missions will
hopefully give us better insight on how our particular magnetosphere behaves, but ours is
not the only system available for study.

Magnetospheres appear to be a somewhat ubiquitous phenomenon among
celestial objects, and this makes sense in the context of current magnetic dynamo theory.
Magnetic dynamos are entities that give rise to internal magnetic fields, and in the
presence of the Sun’s outward plasma stream, these fields form magnetospheres [for
more details about magnetic dynamos, see Finn and Ott (1988)]. This means we should
expect to see a magnetosphere around most of the planets, and we do. Therefore, we can
send spacecraft to other planets and use their magnetospheres as additional laboratories to
better understand what could happen at Earth. The Voyager and Pioneer missions flew by
the gas giants and took the first measurements of extraterrestrial magnetospheres. The
Cassini spacecraft flew by Jupiter in late 2000 and is currently orbiting Saturn, giving
excellent-quality long-term coverage of the system, and it promises to be invaluable as
the data are analyzed. The Galileo spacecraft remained in orbit around Jupiter from 1995 to 2003 to carry out a similar objective. The remainder of this paper will discuss the data it collected, how it can be analyzed and what the physical implications are.

1.4 **What would we expect to see?**

![Figure 1.1 Similar to the Earth, Jupiter's magnetic field is bent by outwardly-streaming plasma from the Sun (solar wind). Unlike the Earth, Jupiter's magnetosphere derives significant power from the planet's rotation and plasma ejected from its moons. [Bagenal, 1992]](image)

The general profile of Jupiter’s magnetosphere is given by Figure 1.1 and described in Chapter 24 of *Jupiter* [2007]. Unlike the Earth’s magnetosphere, which is primarily shaped by the forces from the outward solar plasma stream (known as “solar wind”), Jupiter’s magnetosphere is considered “rotation driven,” meaning that the majority of magnetospheric energy originates from Jupiter’s angular momentum. In the inner magnetosphere [~ 5-30 Jupiter radii (Rj)], the plasma rotates around the planet at the same rate as the magnetic field, a condition called corotation. Also unlike Earth, there
are significant sources of plasma within the magnetosphere, coming primarily from volcanically ejected material from the moon Io. This internal plasma allows Jupiter’s magnetosphere to be much larger than what would result from a dipolar magnetic field with no plasma. Knowing this, we should expect to see a peak in plasma density near Io’s orbit (~5.9 Rj) and some sort of decaying behavior with increasing radial distance. These preliminary expectations helped us to understand when our data analysis was heading in the right direction. However, before we could analyze the data, we first had to understand a few things about the data.

2. DATA

Galileo was the first spacecraft to maintain an orbit in an outer planet’s magnetosphere, and it was a milestone in understanding the dynamics within Jupiter’s magnetosphere. Because no other mission to the gas giant has ever been able to take observations over timescales longer than several days, the information sent back from Galileo remains the largest available data set on the Jovian system, and it is supplemented by simultaneous remote observations made from Earth-based telescopes [Reviewed by Bagenal, 2007]. The Plasma Science instrument (PLS) comprises seven separate anodes, each connecting to the same nested set of three quarter-spherical plate electrostatic analyzers (ESAs). An ESA is essentially two plates with a potential difference between them, and this potential gradient only allows particles with a certain energy-to-charge ratio pass through them. Particles that do not possess this ratio get deflected into one of the plates and thus do not hit the detector. Therefore, the PLS measures a count of how many particles hit the detector, and the ESA puts a constraint on the amount of energy these detected particles can have. The PLS was pre-programmed to step the ESA through
64 different energy values, called energy bins, ranging from 1 eV to ~50 keV. So this instrument, attached to the spun part of the spacecraft, was designed to “sweep” through all 64 energy bins once every spacecraft “spin,” (i.e., rotation period). The seven anodes were spread out in a fan shape on the surface of the PLS, as in Figure 2.1, so that it could obtain three-dimensional spatial resolution over the course of a spin.

![Image](image.png)

**Figure 2.1** The spatial configuration of the seven PLS anodes. Their strange geometries are designed so the electric field in the ESA does not distort due to mechanical impurities. Also, Galileo’s spin direction was actually opposite to what is indicated in the diagram.

Unfortunately, the main antenna of Galileo was not able to open completely, so it was unable to transmit data back to Earth. Engineers managed to transmit everything from the backup low-gain antenna, but this reduced the data transfer rate from 134,000 bps to about 160 bps, which is about as fast as a Morse code operator can send a message [Taylor, 2002]. To sufficiently compress the PLS data for uplink, counts for every fourth energy bin were measured, as opposed to sequentially stepping through each energy bin. This means a full energy sweep would actually take four spacecraft spins, and thus the temporal resolution was reduced by a factor of four. On top of this, although the PLS could measure both ions and electrons, the electron instrument failed on the first orbit, so
we only look at ion data. After everything was properly reorganized, we were left with a total of 114133 so-called “merged spins,” which I will refer to as “records.” From this point, we were able to begin our data analysis.

3. METHOD

3.1 Assumptions

There are several valid ways a given data set can be analyzed. Perhaps if Galileo’s main antenna had deployed properly, the data sent back would have had much better resolution, and it could have allowed us to do much more sophisticated analysis techniques than what we have done here. However, when the data are as noisy and sparse as what was returned from the PLS instrument, fancy and rigorous methods do not yield any better results than basic methods, so there is no sense in doing more work than necessary to get the same answer. Therefore, we made a few assumptions that might not seem reasonable for plasma in the Io torus, but they ultimately do not harm the precision of our final results.

3.11 The Maxwellian Velocity Distribution

We decided that the technique of fitting our data to a theoretical model was the best way to proceed with our analysis. By assuming that the observed plasma was in thermodynamic equilibrium, we must conclude that the plasma should follow a Maxwellian velocity distribution (here, vectors are denoted by boldface):

\[
f(\mathbf{v}) = n \left( \frac{m}{2\pi k_B T} \right)^{3/2} \exp \left( -\frac{m(\mathbf{v} - \mathbf{v}_0)^2}{2k_B T} \right), \quad (3.1)
\]
where \( n \) = ion number density, \( m \) = ion mass, \( T \) = ion temperature, \( \mathbf{v} \) = single ion velocity, \( \mathbf{V}_0 \) = bulk flow velocity, and \( f(\mathbf{v}) \) = ion phase space density. All ions are assumed to have a common bulk flow, \( \mathbf{V}_0 \), which is assumed to be near corotation with Jupiter. This fundamental result from thermodynamics is essentially a Gaussian distribution of individual particle velocities, peaking at the bulk flow velocity with the thermal velocity as the standard deviation. For a given ion species, this theoretical model is uniquely determined by the plasma bulk flow velocity vector (three components), the number density and the temperature. We can adjust these parameters until the curve they produce the best possible fit to the counts data from a single record. From this description, however, we must define what “best possible fit” means, and we have to develop a way to obtain it.

One can get a quantitative measure of how well a curve “fits” the data by summing up all the deviations between the data points and the corresponding points on the curve. To prevent positive and negative deviations from cancelling each other out, we sum the square of these deviations, and dividing by the number of points gives us a sort of average deviation between the curve and the data. The general formula for this average deviation, known as chi-squared, is given by:

\[
\chi^2 = \frac{1}{\nu} \sum_l \frac{(y_f - y_l)^2}{\sigma_l^2} \tag{3.2}
\]

Further details about chi-squared minimization and Equation 3.2 can be found in Bevington [2003], but the important point is that chi-squared gives us a quantitative measure of how good a fit is. Because the Maxwellian is entirely determined by bulk flow, temperature and density, these parameters also determine the value of chi-squared.
If the number of adjustable parameters is $M$, one could imagine that finding the best possible fit amounts to wandering around on an $M$-dimensional chi-squared hypersurface until a global minimum is reached. The parameter values corresponding to this minimum are the best representation of plasma that could produce that record’s counts data.

We can get an estimate of the uncertainties of these parameters through further chi-squared analysis. Very close to the minimum, the chi-squared surface should resemble a parabola when plotted with respect to any of the parameters. The width of the parabola that would approximate the surface in this vicinity gives an estimate of how uncertain that parameter is. The actual calculation of these uncertainties involved numerical approximations of the second derivatives of chi-squared with respect to each parameter, and these details can also be found in Bevington.

3.12 Single species

A Maxwellian curve is determined for a given ion species (in particular, a given mass-to-charge ratio), so it seems we cannot even create a best-fit curve until we make some a priori assumption about the species present in the Io torus. However, the Cassini spacecraft flew by Jupiter between 2000 and 2001 to receive a gravity assist to get to Saturn. During its encounter, the Cassini Ultraviolet Imaging Spectrograph (UVIS) instrument took observations of the UV emissions from sulfur and oxygen ions trapped by Jupiter’s inner magnetic field, creating the so-called Io torus. These observations give us relative abundances for major ion species present. If the data were perfect, we could find individual best-fit Maxwellian curves for each species. However, the data records do not show distinguishable peaks that we could attribute to different ions; they only show the sum of their individual curves, as seen in Figure 3.1.
Figure 3.1 The individual species fits were done independently of the total flux fit. The data cannot tell us which fit is more accurate.

Therefore, we calculated an average mass-to-charge ratio of 13.67 from the UVIS measurements [Delamere, 2005]. This comes from taking the sum of the mass-to-charge ratios of $S^+$, $S^{++}$, $S^{+++}$, $O^+$, and $O^{++}$, with each term weighted by its relative abundance, and dividing that by the sum of the relative abundances. From there, we fit the Maxwellian of this hypothetical single species for each record.

There are also some secondary assumptions we make in order to keep the complexity of our analysis on par with the quality of the data. For example, ordinarily, the ion temperature is separated into temperature due to motion that is either parallel or perpendicular to the magnetic field. Due to the data quality, it is futile to distinguish
between these two temperatures, so we assume the plasma has the same temperature in all directions. In addition, a Maxwellian distribution arises only when plasma is in thermodynamic equilibrium, so when we assume this model is valid, we also implicitly assume that plasma conditions are not changing significantly over the course of a record.

3.2 **Data Pruning**

Because the Maxwellian distribution is entirely determined by five parameters—number density, temperature, and three components of the bulk flow velocity vector—the curve that most closely fits the data within a record gives us the best-fit values of these five parameters. However, “best fit” does not necessarily mean “good fit,” it just means that was the best fit computationally possible for that record. Therefore, it’s entirely plausible that the parameters derived from the fits are totally physically unreasonable, even if we have placed the proper constraints in the fitting routine. This is a potential issue with any finite data set, but the poor quality of the PLS data makes this problem particularly significant.
There is far too much scatter to have any idea of what is going on physically. Low-resolution means the accumulation time of a count measurement was 0.5 seconds. For mid-resolution, the accumulation time was 0.2667 s, and the high-resolution accumulation time was 0.1 s.

The whole reason we want to examine these parameters is to spot trends that correspond to known physical processes, but when the fit values are as scattered as they are in Figure 3.2, there is no chance of understanding what is going on. There seem to be
hints of trend lines in some of the parameters, but we could not say they exist with much confidence. If we believe that the model is correct, then we have to believe that the trends we seek are present, but they are buried underneath a smattering of “bad” data. However, “bad” is an ambiguous term, and if we want to identify which points are “bad,” we must first define what “bad” means. It would be nice if we could simply say the points that are significantly far away from what theory would predict are bad, but this is reckless data selection, which is not science. In order to truly hear what the data have to say, we have to determine “bad” based on how well the fits represent the counts data from which they were generated.

Because chi-squared represents the total deviation of the fit from the data points, we initially assumed that this value alone would determine how good a fit was. In an ideal world, as we lower the maximum chi-squared value of points to be considered, we should eventually see the expected trends emerge from the scatter. However, the PLS data set is not infinite, and as we discard more points, we are left with fewer and fewer points to create trend lines. So, as we lowered our upper limit on acceptable chi-squared values, the number of points left was too small to observe trends anymore. In addition, there always remained a great deal of scatter regardless of how much we lowered our upper chi-squared limit. This forced us to develop more rigorous conditions that would qualify a data point as “bad.”

To find these conditions, we scrutinized the curves of best fit corresponding to these points and searched for patterns. Occasionally, we would look at a record with plenty of data in all anodes and sectors, and that produces a plot like Figure 3.3. The x-axis is just sequential energy bin steps, which translate to time. The high-frequency
wiggles in the fit curve account for the energy bin sweeping, and the low-frequency wiggles account for the physical spinning of the spacecraft relative to the bulk flow direction.

Figure 3.3 Here is an example of a record with very high number of counts above the background level. This makes the data very smooth and easy to fit to, meaning the parameters that determine the fit curve have low uncertainties.

However, plots of this quality were few and far between because most records had much fewer data points, making it more difficult for the fitting routine to generate a best-fit curve for them. As we expected, these curves typically showed extreme deviations from the data points, allowing the best-fit parameter values to be wildly different from what they should be. However, very few points means very few deviations, so the chi-
squared values for these records were deceivingly small. This explained why lowering our acceptable chi-squared limit didn’t eliminate the scatter.

![Figure 3.4 The scatter in the fit parameters is due to most of the counts plots looking like this. Notice how the fit curve peaks where there is nothing, one of the data peaks is one-sided, and most of the record is just background noise.](image)

We also realized that the fit curve does bizarre things when there is very little data to fit to. As you can see from Figure 3.4, there are peaks that only have one side, and sometimes there are peaks that occur where there is no peak in the counts at all, which is a serious problem considering the overwhelming majority of the records do not have many data points. However, Figure 3.4 also shows that a large portion of the data being fit to is just background noise, meaning there is no real data there. If we want to minimize the probability that a fit curve won’t produce a false peak, we do not want our fitting routine to consider points that are too close to the background level. In light of this, we
forced the fits to only consider the anode with the peak number of counts and the neighboring anodes on either side of it. Also, because the width of a Maxwellian peak corresponds to the plasma temperature, one-sided peaks cannot possibly represent actual physical conditions. Therefore, we had our program search for one-sided peaks within record, and if any were discovered, that record wouldn’t even be considered for fitting. These conditions, however, are still not enough to filter out enough “bad” data points to show us clear trends in the plasma parameters. Until this point, we have only imposed criteria that ensure the fit curves are “physical,” which does not necessarily mean they should follow a trend we believe should be there. Nevertheless, we can get an idea of how well a parameter is determined when we compare it to its uncertainty that comes out of the chi-squared analysis. It is difficult to have any confidence in a point that has an error greater than the value itself. Also, if a point has an error that is unrealistically small, this is probably due to a very small number of points with counts above background in a record, so this is just as suspicious as a point with large error. From these principles, we decided that the error-to-value (ETV) ratio of a point is another good way to determine the “badness” of a fit. Based on examining the individual fits again, we decided that an upper ETV limit of 1 and a lower ETV limit of .01 were reasonable. After including all of these conditions together, which we call the “pruning” process, we were successful in obtaining data points that showed clear trends.
Figure 3.4 Our pruning was able to filter out enough scatter to show trends more clearly.

Figure 3.4 allows us to see co-rotation behavior in the azimuthal velocity component (v-phi) and a peak in ion number density (n) near the radius of Io’s orbit, beyond which it decays as an inverse power law. These results indicated to us that our pruning was effective enough to begin analysis on the best-fit values, rather than the counts data.
It might seem strange that there are so few regions where the counts are high enough above background for our fitting routine to consider them, and this is due to the high background level in the region we’re studying. This is caused by energetic electrons diffusing outward from Jupiter’s radiation belts and flooding the PLS detector.

3.3 **Fitting Radial Profiles**

Analogous to the method of fitting a model to the counts data with respect to energy-per-charge, we can fit straight lines to any one of the five plasma parameters with respect to radial distance (R). This is the reason we have chosen to plot the fits on logarithmic axes: to transform any exponential behavior into linear behavior. We could fit the data to a power law curve, i.e. \( f(x) = ax^b \), where “a” and “b” are constants we can adjust to minimize chi-squared. However, if we take the logarithm of this type of equation, we get \( \ln[f(x)] = \ln(ax^b) = \ln(a) + b*\ln(x) \). Now we have an equation that is linear between the logarithms of the variables, which we can redefine as new variables. If we redefine the constants as well, we get the form \( y(x) = A + Bx \). With this completely equivalent equation, we used simple linear regression algorithms to fit the logarithms of the plasma parameters as functions of \( \ln(R) \). This method is preferable to other IDL fitting routines, which use nonlinear models and typically return less accurate best fit results and uncertainties. The difference between these methods is demonstrated in Figures 3.5 and 3.6.

Although we could simply fit the entire data set at once with respect to each plasma parameter and consider the behavior determined, this would be too broad of a stroke. These data were taken over the course of nearly eight years, and there is plenty of temporal variability we might not be seeing unless we examine the data epoch-by-
epoch. In the case of satellite data, a handy characteristic timescale we can use to define an epoch is an orbital period. This makes sense because Galileo’s orbits were never shorter than a couple months, allowing ample time for conditions to change between measurements. For these reasons, we decided to split the data up by orbit number, with each orbit being defined as the time when the satellite passes through apojove. At this point, we could fit straight lines to each of the plasma parameters for each orbit, giving 34 different slopes and intercepts to analyze for variation over time.
Figure 3.5 Best-fit lines made for orbit 6 using IDL CURVEFIT routine in linear space. Error bars were not included in these particular plots because they were not necessary to make the best-fit lines (we could have done this, but we were not confident enough in the uncertainties of the parameters). Significant figures were neglected in creating these plots.
3.4 **Two-dimensional extrapolation**

We have been able to develop a method for one-dimensional analysis of the fits, and they give us a decent, if not somewhat abstract, picture of how the plasma is
distributed in Jupiter’s inner magnetosphere (by its density). If we want to extend this analysis to higher dimensions, we have to get creative.

Unfortunately, Galileo never deviated more than a few degrees in latitude from the equator, so we are left with nearly no information about theta dependences. However, because the plasma tends to co-rotate with Jupiter, it feels an associated centrifugal force that tends to fling it radially outward from the rotation axis, and, for a dipolar field, a given field line is farthest from the planet at the equator [Bagenal, 2011]. Therefore, we should expect the density to peak near the equator and decay above and below it. The density distribution as a function of height, z, away from the equator can be solved analytically for small z, and it is given by [Hill and Michel, 1976]

\[ n(z) = n_0 e^{-(z/H)^2}, \]

\[ H = \left[ \frac{2}{3} \kappa T_i (m_p A_i \Omega^2) \right]^{1/2} = H_0[T_i/A_i]^{1/2} \]

Here, \( \Omega \) = Jupiter’s rotation rate = 9.925 hours, \( m_p \) = mass of a proton, \( H_0 = .64 \) Rj, \( T_i \) is the ion temperature in eV, and \( A_i \) is the average ion mass in amu. With our best fit lines for density we can determine \( n_0 \) with respect to R, and because we also have the temperature best fit lines versus R, we can determine the scale height H as a function of R—which forces the assumption that the temperature doesn’t vary too much with latitude. Therefore, this extrapolation determines the density for all z and R, allowing us to create two-dimensional profiles of the plasma distribution, which will be discussed in Section 4.5.
4. RESULTS

4.1 Demonstrating the Effects of Pruning

Figure 4.1 Fit values over entire Galileo mission, without pruning. Colors represent the local time sector in which each record was taken. Green = dawn (3 – 9 hrs), Red = noon (9-15 hrs), Violet = dusk (15-21 hrs), and Blue = midnight (21 hrs – 3 hrs)
Figure 4.2 Fit values over entire Galileo mission, with pruning

By looking at the fit curves in the individual counts data records, we were able to identify several recurring features that severely skewed the fits and made them return unbelievable plasma parameters. When we programmed the fitting routine to correct for these features, the fits returned plasma parameters that were believable enough to continue analysis on them. To ensure that these fits had actually improved, we returned to
a few more of these records that had survived pruning, and we were convinced the fits were sufficiently close to the counts data. So even if we could not obtain any significant scientific results from the data analysis, at least we can be sure that our pruning process is efficient enough to make sense of bad data.

4.2 **Factoring in Trajectory Information**

It is relatively simple to identify variability in plasma conditions over time without considering what might cause those variations. However, because the plasma also varies in space, we have to keep in mind effects from the position of the spacecraft itself before we can say much about the physical processes going on. Therefore, we plot Galileo’s trajectory information, obtained from the University of Iowa ephemeris website, along with the plasma parameters.
4.3 Other position variables contain additional information

Thus far, the data have only been analyzed with respect to radial distance, but there are several other spatial coordinates we could also use as independent variables. If
we want to get the most comprehensive understanding possible of spatial variability, we should plot the plasma parameters with respect to each of these coordinates.

Figure 4.4 Keeping trajectory information juxtaposed with the plasma parameters helps us determine the sources of some effects.
Figure 4.5 Plasma parameters and trajectory with respect to spacecraft latitude
Figure 4.6 Plasma parameters and spacecraft trajectory with respect to local time
4.4 **Best-fit line variations with time**

We calculated best-fit lines for the best-fit parameters vs. R in each orbit, and an example is given in Figure 4.7. This gave us 34 different slopes and intercepts for both density and temperature, allowing us to plot how these fit lines varied between orbits, i.e., temporal variability, which is shown in Figure 4.8.

![Figure 4.7](image_url)

*Figure 4.7 Getting lines of best fit for the temperature, density and azimuthal speed with respect to R give us a first-order measure of these parameters’ spatial distributions.*
Figure 4.8 Temporal variations in the best-fit lines. From the top plot downward, this shows the temperature best-fit line’s y-intercept (with units of eV), then its slope (unitless), then the density best-fit line’s y-intercept (units of m⁻³), and then its slope (unitless). TA and TS stand for “temperature amplitude” and “temperature slope,” and NA and NS follow the same convention for density.
The y-intercepts for the best-fit lines varied quite a bit because not all orbits had the same coverage. For example, as seen in Figure 4.9, Galileo only took measurements between 5 and 8 Rj during orbit 0 (orbital insertion), so the behavior of the plasma beyond 8 Rj couldn’t be incorporated. This caused the fit lines in this orbit to be more skewed than those in other orbits with more coverage. This demonstrates the need to fit the density to multiple lines with different intercepts and slopes in order to account for all behavior between 5 and 30 Rj, which is done in [Bagenal, 2011]. However, the slopes of the fit lines showed much less temporal variation than the y-intercepts, having average values of \((2 \pm 1.2)\) for the temperature and \((-6 \pm 2.5)\) for the density. At the very least, this is in agreement with other reports of ion temperature increasing with radial distance in the Io plasma torus [Bagenal, 2007]. These averages were used to construct a two-dimensional profile of the plasma density, which is shown in Figure 4.10.
Figure 4.9 Orbits with small coverage ranges can have much different best-fit lines than orbits with wider coverage.
4.5 Best-fit lines for each local time over whole mission

Krupp et. al. [2001] have suggested, using energetic particle data, that there should be a strong asymmetry between the azimuthal flow speeds (v-phi) in the dawn and dusk sectors on the order of ~100 km/s. If this is true, we should be able to see significant differences in the best-fit lines for v-phi if we separate data points by local time sectors. Figures 4.11-14 show the best-fit lines for dawn, noon, dusk and midnight, respectively.
Figure 4.10 Best-fit lines for all mission data recorded in the dawn sector
Figure 4.11 Best-fit lines for all mission data recorded in the noon sector
Figure 4.12 Best-fit lines for all mission data recorded in the dusk sector
From these plots, we can see slight differences between the best-fit lines for v-phi in each sector. However, as seen in previous plots, these differences are more likely to
come from coverage differences rather than physical asymmetries. No consistent asymmetry on the order of 100 km/s was found in v-phi, and the largest uncertainties in the fits are on the order of ~10 km/s. Therefore, this data seems to refute the results of Krupp, Woch, et. al. Nevertheless, we can still look for asymmetries in density or temperature, and to illustrate these potential asymmetries, we again constructed a two-dimensional density profile for each local time sector. Figures 4.15 shows the density profiles corresponding to each local time sector.
Figure 4.15 Two-dimensional density profiles constructed from the best-fit lines for each local time sector over the entire Galileo mission. From left to right, the top two plots correspond to dawn and noon, and the bottom two plots correspond to dusk and midnight.

From these profiles, there appears to be no significant variation in the density or temperature (which affects the width of the distribution) with respect to local time.
5. CONCLUSION

Data analysis is a tricky beast. One has to simultaneously align the measurements with expected results while not throwing out information that could potentially contradict expectations. After all, most scientific breakthroughs begin with measurements that contradict popular belief. To make matters worse for the particular case of Galileo PLS data, most of the records have little to no counts above background, so there are very little data to fit to. Eliminating bad points altogether would leave us with too few points to display trends, which would be throwing the baby out with the bathwater. Therefore, we had to specially tailor our pruning to sift out bad parts of individual records, not the whole records themselves. Once we fit trend lines to the points that survived pruning, we began to see theoretically expected behavior.

We did not detect any significant variations in the plasma conditions over the time of the Galileo mission, but this conclusion may have been different if each orbit had equal coverage. The spatial variations in the plasma parameters followed trends that agreed with [Delamere, 2005] and [Bagenal, 2007], although we did not find any local time asymmetries comparable to what was found by [Krupp, 2001].
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