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**Solar wind prediction for the Parker Solar Probe orbit**

**Near-Sun extrapolations derived from an empirical solar wind model based on Helios and OMNI observations**

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**ABSTRACT**

*Context. The Parker Solar Probe (PSP) (formerly Solar Probe Plus) mission will be humanity's first in-situ exploration of the corona of a star to help answer hitherto unresolved science questions on the heating of the solar corona and origin and acceleration of the solar wind, its structure and dynamics and the acceleration of solar energetic particles. PSP is currently scheduled for launch in mid 2018. CGAUSS (Coronagraphic German And US Solar Probe Survey) is the German contribution to the mission as part of the Wide field Imager for Solar PRobe (WISPR). Within the CGAUSS project the solar wind environment is extrapolated down to the closest perihelion of 9.86 solar radii distance to the Sun using in situ solar wind data from the German-US Helios 1 and 2 space probes, including 1 AU data from various satellites compiled in the NASA/GSFC OMNI solar wind database.*

*Aims.* We present the development of an empirical solar wind model for the inner heliosphere which is derived from Helios and OMNI in situ data. The space probes Helios 1 and Helios 2 flew in the 1970s and observed solar wind in the ecliptic within heliocentric distances of 0.29–0.98 AU. The OMNI data set at NASA's Space Physics Data Facility (SPDF) consists of multi-spacecraft intercalibrated in situ data obtained near 1 AU. The solar wind model is used together with sunspot number predictions to estimate the frequency distributions of major solar wind parameters PSP will encounter during its mission.

*Methods.* The established model covers the solar wind’s magnetic field strength and its plasma parameters proton density, velocity and temper- ature. Their individual frequency distributions are represented with lognormal functions. In addition, we also consider the velocity distribution’s bi-componental shape, consisting of a slower and a faster part. The model accounts for solar activity and for solar dis- tance dependency by shifting of these lognormal distributions nicht klar. We take into account dependencies on solar activity by correlating and fitting the frequency distributions with the sunspot number (SSN), using almost five solar cycles of OMNI data. Further, based on the combined data set from both Helios probes, the parameters’ frequency distributions are fitted with respect to solar distance to obtain exponential dependencies. Finally, by combining the found solar cycle and solar distance relations, we obtain a simple dynamical solar wind model for the inner heliosphere, confined to the ecliptic region.

*Results.* The inclusion of SSN predictions and the extrapolation to the PSP perihelion region enables us to estimate the solar wind environment for the PSP prime mission time 2018-2026. The estimated solar wind values at PSP’s nearest perihelion are: ... Their values vary up to 0.0000 %, arising only from differing amplitude assumptions for the next solar cycle.

**Key words.** solar wind – sun: heliosphere – sun: corona

# Introduction

With his theoretical solar wind model Parker (1958) formulated the existence of the solar wind even before the first satellites measured it in-situ in 1962 (ref.). Almost at the same time the presence of a continuous flow of particles from the Sun was inferred from observations of cometary tail fluctuations (ref.). The idea of a space mission flying through the solar corona dates back to the founding year of NASA in 1958 (ref.). Since then space missions like Helios 1 and 2, and Voyager 1 and 2 have measured the solar wind in-situ at distances as close to the Sun as 0.29 AU and as far away as 137 AU, having even left leaving the heliosphere itself as in the case of Voyager 1 (ref.). Ulysses was the first mission that measured the solar wind out of the ecliptic plane and over the poles of the Sun (ref.). Sun outside the ecliptic and retrieving solar wind measurements from the poles of the Sun. So far, Helios 2 made the nearest in situ solar wind measurements ever at a distance of 0.29 AU, closely followed by Helios 1 with 0.31 AU. The Parker Solar Probe (PSP), with a planned launch date in mid 2018, will reach after seven years in 2025 a distance of 9.86 RS, i.e. 0.047 AU through several Venus gravity assists. Each orbit has a duration of about 88 days. In summary PSP provides 24 orbits with perihels inside 0.25 AU. It will be humanity’s first space probe flying through the solar corona, providing the first in-situ measurements of the coronal and near-Sun solar wind plasma and magnetic field parameters and the properties of solar energetic particles, as well as their structures and dynamics. The key PSP science objectives are to “trace the flow of energy that heats and accelerates the solar corona and solar wind, determine the structure and dynamics of the plasma and magnetic fields at the sources of the solar wind, and explore mechanisms that accelerate and transport energetic particles” (ref.1 NASA STDT report, ref.2 Fox et al). To achieve these goals, PSP has four scientific instruments on board: FIELDS for the measurements of magnetic fields and AC/DC electric fields, SWEAP for the measurements of flux of electrons, protons and alphas, ISIS for the measurement of solar energetic particles and WISPR for the measurement of coronal structures (ref. to each instrument paper). The Wide field Imager for Solar Probe (WISPR) will contribute to the science goals by deriving the 3D structure of the solar corona through which the in-situ measurements are made to determine the sources of the solar wind. It will provide density power spectra over a wide range of structures, e.g., streamers and pseudostreamers, equatorial coronal holes, for determining the roles of turbulence, waves, and pressure-balanced structures in the solar wind. It will also measure the physical properties, such as speed and density jumps, of SEP-producing shocks and their CME drivers as they evolve in the corona and inner heliosphere (ref. Vourlidas et al., 20xx). CGAUSS (Coronagraphic German And US Solar Probe Survey) is the German contribution to the PSP mission as part of the Wide field Imager for Solar PRobe (WISPR). One of the objectives of the CGAUSS project is to extrapolate the solar wind environment down to the closest perihelion of 9.86 solar radii distance to the Sun in order to optimize the WISPR and PSP science operations. To achieve this goal this study uses for this approach in situ solar wind data from the US-German Helios 1 and 2 space probes and 1 AU data from various satellites compiled in the NASA/GSFC OMNI solar wind database.

In section 2 we …, in section will …

# Solar wind environment

As baseline we treat the solar wind primarily as a proton plasma, because the average helium abundance is only about 4.5 % and in slow wind at solar cycle minimum even less than 2 % (Feldman et al. 1978; Schwenn 1983; Kasper et al. 2012). Neglecting heavier ions, the electron and mass density can then be derived ….

The characteristic behavior of a magnetized plasma is deter- mined by its *density*, *temperature and magnetic field strength (ref.)*. Furthermore, the bulk flow *velocity* is the parameter which makes the plasma a ’wind’. For this study we define the solar wind envi- ronment through the four major solar wind parameters a, b, c, d. Quantities like flux densities, mass flux and plasma beta can directly be derived from those four parameters (ref.). Generally two types of solar wind are observed in the heliosphere as slow and fast streams (ref. Neugebauer 1962, Schwenn, McComas et al.). Fast streams are found to originate from coronal holes (ref.) whereas the origin of slow wind is a subject of controversial discussions because several sources are closed magnetic structures in the solar corona, such as Schwenn has even reported the possibility of four types of solar wind depending on the phase of the solar cycle/activity. The solar wind velocity is the defining parameter of the two types of solar wind. Slow solar wind has typical speeds of … km/s and fast solar wind has speeds …. km/s (ref. s. Buch). Their different compositions and characteristics indicate different sources and generation pro- cesses (ref. in McGregor et al. 2011b). Their occurrence frequency varies with the solar activity cycle and their interactions lead to phenomena such as stream interaction regions (SIRs) and for quasi-stationary coronal source regions to co-rotating interaction regions (CIRs, ref. Buch über CIRs).

Superimposed on the slow and fast wind streams are coronal mass ejections (CMEs, ref.). Their frequency in near 1 AU measurements varies between almost zero during solar cycle minima ~~up to a daily rate of about 0.5 during times of solar maximum (Richardson & Cane 2012). This study averages over these internal solar wind structures. Since one~~ cannot know which specific solar wind type or struc-ture PSP will encounter at a given point in time during its mission, we extrapolate the parameters’ probability distributions from existing solar wind measurements.

Our approach is to get an analytical representation of the fre- quency distributions’ shapes, their solar activity dependence and their solar distance scaling. We get the parameters’ frequency distributions and solar activity dependence from near-Earth so- lar wind and sunspot number (SSN) time series with a duration of almost five solar cycles and their distance dependency from solar wind measurements of more than half a solar cycle, cover- ing more than two third of the distance to the Sun (0.29–0.98 au). From the combination of the obtained frequency distribu- tions, SSN dependence functions and solar distance dependence functions we build a general model representing the solar activity

The data is obtained from the OMNIWeb interface1 at NASA’s Space Physics Data Facility (SPDF), Goddard Space Flight Center (GSFC). The hourly data of the whole time range up to 2016-12-31 is the basis for the frequency fits. The data starts in 1963-11-27, but the temperature data not before 1965-07-26. The data coverage of the parameters is between 67– 74 %, which adds up to about 36–40 years in total. This plethora of data is well suited for our task.

We note that the use of higher time resolution instead, would not significantly change our results. The frequency distributions of the also available minutely OMNI data set are almost con- gruent with the hourly—they only differ slightly at their extreme ends.

We specify bin sizes considering the individual maximal pa- rameter ranges and the OMNI data precision. Especially for the density and temperature we choose their bin sizes such small that their distributions’ peaks can be resolved (the peaks are at their lower end). We set the individual bin sizes to 0.5 nT for the magnetic field strength, 10 km s−1 for the velocity, 1 cm−3 for the density and 10 000 K for the temperature.

Next, we look for a suitable fit function for the resulting his- togram shape of the solar wind parameters’ frequency distribu- tions.

*3.2. Lognormal fitting*

Obviously all possible values for the four parameters are posi- tive. This hints to the supposition that they are lognormally dis- tributed, as many positive natural quantities conform to lognor- mal distributions. Its probability density function is described by a lognormal function. Therefore we use a lognormal function as the fit function in the process of the least squares regression fit- ting. The lognormal function

and distance behavior of all four solar wind parameter frequen- cies.

This general model is then fed with a SSN prediction and

*W*(*x*)

1

σ √2π*x* −

exp I=

(ln *x* − µ)2 (1)

2σ2

\

extrapolated to PSP’s planned orbital positions.

# Frequency distributions

This section looks at the solar wind parameters’ frequency dis- tributions which we extract from the in situ OMNI data set. We

depends on the location µ and the shape parameter σ. Changes in µ affect both the horizontal and vertical scaling of the function whereas σ influences its shape. The distribution’s median *x*med and mean *x*avg (average) positions are easier to interprete and can directly be calculated from µ and σ:

*x*med = exp (µ) ⇐⇒ µ = ln (*x*med) , (2)

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determine adequate fit function types and evaluate how suitable they are to represent the frequencies’ shapes.

*x*avg = exp

µ + σ

2

2

⇐⇒ σ =

2 ln

*x*avg

*x*med

. (3)

*3.1. OMNI frequency data*

The solar wind parameters are highly variable, due to short- term variations from structures like slow and fast wind streams,

It is apparent that the mean is always larger than the median. Re- placing the variables µ and σ with these relations, the lognormal function (1) becomes

interaction regions and CMEs, whose rate and properties de-

pend on solar activity. Hence, for deriving general frequency

/π ln

(

)

exp −



med . (4)

( )  *x*avg

*x*med

*W*(*x*) =

distributions of the solar wind parameters, averaging over long- term solar wind variations is needed. This requires a distance-

1 

2

*x*avg

*x*med

*x*

ln2 ( *x x*

4 ln

) 

2

*x*avg

*x*med

*x*

4 ln

independent data set covering multiple solar cycles. The abun- dance of near-Earth hourly OMNI data is well suited for this task, because it spans almost five solar cycles.

This OMNI 2 data set (King & Papitashvili 2005) combines solar wind plasma and magnetic field data and for this study not important energetic proton fluxes, geomagnetic and solar in- dices. Because it covers decades, the near-Earth solar wind data

The values of *x*med and *x*avg obtained from fitting the solar wind frequency distributions are listed in Table 1.

From visual inspection, the resulting curves match well with the shape of the magnetic field strength, density and temperature distributions (Fig. 1). However, for the velocity the fit function seems insufficient in describing its more complex shape, espe- cially at its peak position and the faster end of the distribution. Its

is composed of intercalibrated multi-spacecraft data which is

time-shifted to the nose of the Earth’s bow shock.

1 <http://omniweb.gsfc.nasa.gov/>

**Table 1.** Resulting fit coefficients from the fitting of the lognormal function (4) to the shape of the solar wind parameters’ frequency distributions at 1 au (OMNI hourly data). For the velocity also the fit parameters from the double lognormal function (5) are given, as well as the median and mean values of the resulting velocity fit. The mean absolute errors and sums of absolute residuals are shown as well. The values in brackets are the estimated standard deviation of each fit parameter.

*x*med *x*avg *c* [%]

|  |  |  |  |
| --- | --- | --- | --- |
| Parameter Median*a* | | Mean*a* Balance MAE SAR | |
| Magnetic field 5.661(16) | | 6.164(18) | – 5.51 × 10−4 6.83 |
| Velocity 4.085(19) | | 4.183(20) | – 1.80 × 10−3 18.69 |
| Density 5.276(24) | | 6.484(34) | – 5.49 × 10−4 6.48 |
| Temperature 7.470(17) | | 11.301(32) | – 8.71 × 10−5 5.78 |
| Velocity *W*1 | 4.89(14)  3.68(20) | 5.00(14) 0.504(62) – – | |
| *W*II | 4.16(14)*b* | 4.42(14)*b* | – 3.98 × 10−4 4.20 |

*W*2 3.72(20) – –

**Notes.** (*a*) Values in their respective units nT, 102 km s−1, cm−3 and 104 K. (*b*) Error estimates derived from the individual fit part errors.

figures/histogram\_fits\_4\_a\_zoom\_paper\_pdfplot.pdf

**Fig. 1.** Frequency distributions of the four solar wind parameters and their lognormal fits. The histograms have bins of 0.5 nT, 10 km/s, 1 cm−3 and 10 000 K and are based on the hourly OMNI data set. The fit’s median and mean values are indicated as well. The insets only have zoomed-in frequency axes, their x-axes stay the same.

sum of absolute residuals (SAR) between data and fit is almost three times larger than those from the other parameters (Table 1). They can be compared, because the area of probability density functions is unity.

To reach a better fit result for the velocity we change the fit function. We do not want to abandon the well-founded appli- cation of the lognormal function. However, it is reasonable to assume that the velocity distribution can be made up of at least two overlapping branches (McGregor et al. 2011a). Therefore a compositional approach promises better fit results, which is why we combine two lognormal functions (4), bearing the disadvan-

tage of more fit variables:

*W*II(*x*) = *c* · *W*1(*x*) + (1 − *c*) · *W*2(*x*) . (5)

The balancing parameter *c* ensures that the resulting function remains normalized as it represents a probability distribution.

The fitting of *W*II(*x*) to the velocity’s frequency distribution gives the values of the now five fit parameters (*c*, *x*med,1, *x*avg,1, *x*med,2 and *x*avg,2), which are also listed in Table 1 together with the median and mean of the composed distribution, which can

figures/histogram\_fits\_V\_a\_zoom\_dbl\_paper\_pdfplot.pdf

figures/OMNI\_yearly\_ssn\_correlation\_c\_plot.pdf

**Fig. 2.** Plot of the velocity’s frequency distribution (same as in Fig. 1) and its compositional lognormal fit. The fit’s median and mean values and its two fit parts are indicated as well. The inset only has a zoomed-in frequency axis, its x-axis stays the same.

be derived via solving

r *W*II(*x*) d*x* = 0 and r *x W*II(*x*) d*x* = 0 (6) respectively.

As anticipated, this more complex fit function is more accurate in describing the velocity’s frequency distribution (see Fig. 2). For this reason we keep using the double lognormal ansatz for the velocity frequency fits in the following sections.

In this static model the slow and fast part contribute almost equally (*c* 0.5), which of course is only valid for this kind of long-term average. At different times in a solar cycle their contributions vary strongly.

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For the bulk of the solar wind these static lognormal func- tions describe the parameters’ distributions well. This is differ- ent for the extreme values (which may also stem from CMEs). The simple lognormal fit models of the magnetic field strength, the velocity and the density underestimate their frequency at the high value tails, whereas the temperature’s tail is overestimated (see insets of Fig. 1). The velocity’s compositional lognormal fit only slightly overestimates its tail (inset in Fig. 2).

Short-term variations in the solar wind cannot be predicted, but their occurrence rate can. It depends on solar activity, which changes cyclically and thus can be forecasted to a certain degree—at least within a solar cycle.

# Solar activity variations

This section aims to relate changes in the four solar wind param- eters to general solar activity. For this we examine their correla- tions to the yearly sunspot number and determine the lag times with the highest coefficients. Next, we fit lognormal functions to the frequency distributions like before, but implement linear re- lations to the yearly SSN to shift the distributions. Only for the velocity the approach is different in that its two components are

**Fig. 3.** Plot of the solar wind parameter yearly medians from OMNI data and the yearly SSN from the SILSO World Data Center (1963– 2016) with cycle number (top). Their correlation coefficients with the yearly SSN are calculated for time lags back to -15 years (bottom).

* 1. *SSN data*

Solar activity is commonly measured via the sunspot number. We want to correlate OMNI in situ measurements with the SSN, yet OMNI data are from Earth orbit, causing variations in solar latitude and distance. To dodge these seasonal variations we use yearly OMNI and SSN data.

The international sunspot number (1963–2016) is retrieved from the online catalogue2 at the World Data Center – Sunspot Index and Long-term Solar Observations (WDC-SILSO), Solar Influences Data Analysis Center (SIDC), Royal Observatory of Belgium (ROB).

* 1. *SSN correlation*

Our current interest lies in the correlation of the SSN to the solar wind median values, because the median defines the position of a lognormal function. The yearly OMNI parameter medians and the yearly SSN are plotted in Fig. 3.

The solar wind velocity and its close friends density and tem- perature are known to depend on the state of the solar cycle (Schwenn 1983), which is why they follow the SSN indirectly (with time lag). Thus we derive the correlation coefficients for different time lags between solar wind parameters and SSN (see Fig. 3).

The highest correlation coefficient for the magnetic field strength is 0.728, which is without lag time and the highest of

kept fixed and instead their balance is modified with changing

SSN.

2 <http://www.sidc.be/silso/>

figures/Vdbl\_SSN\_ratio\_f\_plot.pdf

**Fig. 5.** Solar wind parameter median over lagged SSN. The yearly data medians (+) with their weighted linear fit (solid) are obtained from OMNI data. The error bars denote the SSN standard deviation and the relative weight from the yearly data coverage. The SSN dependent me- dian (7) is from the lognormal model fit (dashed). For the velocity the median is derived from the SSN weighting of the slow and fast model parts, whose magnitudes are SSN independent (dotted).

figures/OMNI\_yearly\_BVNTvsSSN\_a.pdf

all solar wind parameters. This is anticipated because the SSN is directly proportional to the magnetic flux (Smith & Balogh 2003).

Velocity and temperature have a lag time of 3 years with their maximal correlation coefficients (0.453 and 0.540). The density has a lag time of 6 years (0.468), which is in agreement with the by Bougeret et al. (1984) documented density anticorrelation with SSN.

As expected, the correlation coefficients’ amplitudes of all parameters decline with increasing lag time and show a fre- quency of about 11 years.

* 1. *SSN fitting*

To be able to shift the frequency distributions with SSN, we add a linear SSN dependency to the median

*x*med(*ssn*) = *a*med · *ssn* + *b*med , (7)

using a factor to the SSN *a*med with a baseline *b*med. We relate the mean with a scaling factor to the median to transfer its SSN dependency:

*x*avg(*ssn*) = (1 + *a*avg) · *x*med(*ssn*) . (8)

With the implementation of these relations into the lognor- mal function (4), the new dynamic fit function *W*,(*x*, *ssn*) is then fitted to the yearly data. The three resulting fit coefficients (*a*med, *b*med and *a*avg) are presented in Table 2.

Naturally, the fit models match with the general data trends, though single year variations are not able to be replicated by the model (e.g. the high velocity and temperature values in 1974, 1994 and 2003) (see Fig. 4). The comparison with the yearly data median values over SSN shows that the from the model obtained medians have a quite similar slope (see Fig. 5).

Again, the velocity gets a special treatment with the double lognormal distribution (5). It is known that slow and fast solar wind stream occurrence rates follow the solar cycle, yet their

**Fig. 6.** Balance of slow to fast solar wind over the by 3 years lagged SSN. The yearly ratios (+) and their weighted linear fit (solid) are ob- tained from OMNI data with a threshold velocity of vth = 400 km s−1. The error bars denote the SSN standard deviation and the relative weight from the yearly data coverage. The model’s balance parameter (9) and derived ratio (same threshold) are plotted as dashed and dotted lines.

magnitudes stay fairly stable (cite?). Thus we keep the two ve- locity components’ positions constant and vary instead their bal- ance with the SSN:

*c*(*ssn*) = *ca* · *ssn* + *cb* . (9)

The fit result (see Table 2) is a model in which three years after solar cycle minimum (SSN of zero) the slow solar wind has a share of almost two-thirds and decreases further with increasing SSN (see Fig. 6).

To compare the ratios of slow to fast wind between model and data, we simply apply the commonly used constant veloc- ity threshold of vth = 400 km s−1 (cite?). The linear fit to the yearly data ratio and the derived model ratio are quite similar (see Fig. 6). Specific velocity thresholds between slow and fast

solar wind cannot be directly compared with the to some degree steeper balance parameter of this model. The model’s balance may represent the actual ratios of the solar wind types in a more realistic way than a specific velocity threshold does, since the velocity ranges of both types overlap (McGregor et al. 2011a).

# Solar distance dependency

In this section we use Helios data to obtain exponential fit func- tions for the heliocentric distance dependency and also evaluate the fits’ extrapolation behavior in direction to the Sun. To fit the bulk solar wind distributions’ distance dependency we use the frequency fitting method from Sect. 3 on distance-binned Helios data. This results in models comprising of exponentially with distance shifted lognormal functions.

* 1. *Helios distance data*

The Helios probes were the only spacecraft measuring in situ solar wind over large solar distance ranges in the inner helio- sphere. We use the combined data from both Helios 1 and He- lios 2 probes. Helios 1’s (Helios 2’s) highly elliptical orbit in the ecliptic covered a solar distance range of 0.31–0.98 au (0.29–

0.98 au). Launched during solar cycle minimum, the data of both probes cover the rise to the maximum of cycle 21 ( 6.5 years at varying distances).

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Again we choose data with hourly resolution to allow its use along with the hourly OMNI data. As Schwenn (1983) pointed out, the many hourly Helios data points which contain only a few measurements, contribute with a larger scatter to the frequency

**Table 2.** Resulting fit coefficients from the OMNI data fitting with lagged SSN. For the velocity the fit parameters from the double lognormal fit and their balancing function are given. The values in brackets are the estimated standard deviation of each fit parameter.

Median*a* Mean*a*  Balance SSN factor *a*med Baseline *b*med Scaling factor *a*avg SSN factor *ca* Baseline *cb*

Magnetic field 1.309(19) × 10−2 4.285(17) 8.786(78) × 10−2 – –

Parameter

Density 3.81(25) × 10−3 4.495(26) 3.050(27) × 10−1 – –

Temperature 1.974(26) × 10−2 5.729(19) 6.541(28) × 10−1 – –

−1.799(95) × 10− 0.638(32)

Velocity *W*1,

*W*2,

– 3.633(12) 1.008(37) × 10−2 3

– 4.831(81) 2.31(20) × 10−2

**Notes.** (*a*) Values in their respective units nT, 102 km s−1, cm−3 and 104 K.

figures/OMNI\_yearly\_BVdblNTSSN\_fit\_e\_plot.pdf

**Fig. 4.** Solar wind parameter data frequencies, lognormal fit models with their median values (white) and the corresponding yearly SSN (grey) over the OMNI time period 1963–2016. The for the models shifted SSN is indicated by a black line. The velocity median is derived from the SSN weighted constant lognormal parts (dotted).

distributions, nevertheless their effect is insignificant in the treat- ment of the bulk data.

Helios 1’s (Helios 2’s) merged hourly data set from the mag- netometer and plasma instruments (Rosenbauer et al. 1977) in- cludes 12.5 orbits ( 8 orbits) in the time range 1974-12-10 to 1981-06-14 (1976-01-01 to 1980-03-04). The Helios data was retrieved from the Coordinated Data Analysis Web (CDAWeb) interface at NASA’s GSFC/SPDF3.

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The Helios 1 (Helios 2) magnetometer data coverage is about 43 % (54 %) and amounts to 2.8 years (2.3 years) in total. The plasma data coverage is 76 % (92 %) and amounts to 5.0 years (3.9 years) in total. Thus, the Helios data cover only fractions of a solar cycle and cannot be used for deriving representative time-

3 <http://spdf.gsfc.nasa.gov/>

independent solar wind multi-cycle conditions like the OMNI data can.

Using this data, we also have to keep in mind that its time coverage is unequally distributed over the solar cycle. Dividing the data by the transition from cycle minimum to maximum (mid 1977) and considering the data gap distributions, the Helios data covers about 68 % during cycle minimum whereas during maxi- mum only 38 %.

For calculating the median and mean values at different solar distances the data is binned into 0.01 au bins, which is also the native precision in this data set.

* 1. *Exponential fitting*

An exponential distance behavior is expected from all four pa- rameters (cites?). Therefore we use the exponential function

*x*(*r*) = *d re* (10)

with the solar distance *r* for the regression fit of the median and mean. The fits are weighted by data counts per bin. With *r* in astronomical units we get the fit coefficients (*d*med, *d*avg, *e*med and *e*avg) as given in Table 3.

As expected, the velocity exponents match with those from Schwenn (1983, 1990), who derived the distance dependen- cies for both Helios spacecraft separately (vH1(*r*) *r*0.083 and vH2(*r*) *r*0.036). Likewise, the density exponents agree well with the Helios plasma density model, which Bougeret et al. (1984) derived from Helios data and normed to the 1976 1 au density (*n*(*r*) = 6.14 *r*−2.10 cm−3).

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∝

The next step is to fit the bulk of the solar wind parameters with lognormal functions. At all considered solar distances the mean of the three plasma parameters is larger than their median (Fig. 7).

The large velocity’s crossing distance and its large error indi- cate that the median’s and mean’s distance behavior can be kept identical and so the frequency’s shape distance independent.

However, the magnetic field strength’s mean crosses the me- dian at 0.339 au and is lower at smaller distances (Table 3). At the crossing point and below the magnetic field strength can therefore not be described anymore with a lognormal function. For an extrapolation to the PSP perihelion the same happens for the temperature at 0.082 au.

Those crossings limit the possible extrapolation distances with lognormal functions. To circumvent these limitations for all four solar wind parameters we set the exponents *e*med and *e*avg to be identical, avoiding crossing of median and mean. Then the distribution’s width scales exponentially with solar distance. Applying this approximation, we have to accept larger model er- rors, especially for the magnetic field strength. It also limits the extrapolation accuracy, however it keeps the model simpler.

* 1. *Exponential lognormal fitting*

To retrieve the frequency distributions for every 0.01 au solar dis- tance bin, we choose the same solar wind parameter binning as with the OMNI data (Sect. 3.1).

As mentioned before, we set the exponents of median and average to be identical. Implementing the exponential distance dependency (10) into the lognormal function (4), we get three fit parameters (*d*m, ed, *d*a,vg and the common exponent *e*,). Naturally,

we use the double lognormal function (5) for the velocity distri-

bution fit, resulting in *W*I,I,(*x*, *r*). The additional fit parameters are the balancing parameter *c*, and from the second lognormal part

*d*m, ed,2 and *d*a,vg,2. The resulting fit coefficients for the four solar wind parameters are presented in Table 4.

With *c*, = 0.557 the velocity balancing parameter is of an ex- pected value similar to that obtained from the Helios time period (the mean SSN during the Helios period was 59, this corresponds to *c*(59) = 0.53; see Fig. 6).

The fit models seem to resemble the data quite well (Fig. 8). The magnetic field strength frequency is more focused (around 40 nT) at the lower distance boundary than the model’s is. This is expected because of our fixed distance independent shape ap- proximation. The velocity and temperature models’ upper values have a higher frequency than the data shows. This is due to the

figures/yearly\_gradients\_b.pdf

**Fig. 9.** Helios year variation of the solar wind parameters’ fit exponents and SIDC 13-month smoothed monthly SSN. In this plot the year 1974 is omitted because the 21 days covered only

systematic fit discrepancy of the lognormal distribution’s high value tails (see zoom box in Fig. 1).

* 1. *Distance scaling law variations*

relocate section to 5.3?

This radial solar wind model represents the Helios time frame around the rise of solar cycle 21. It is known that the solar wind parameters’ magnitudes vary with solar activity. Looking at the variation of the yearly distance scaling laws (Fig. 9), there is no systematic variation for the magnetic field. The exponents of velocity and temperature seem to follow the SSN and the den- sity not...

For simplicity we assume that the distance scaling laws are time independent and account for this approximation with including the calculated exponents’ yearly variations (Table 3) as uncertainities.

make remark about influence of unequal solar cycle cover- age... (sect. 5.1)

Possible differing scaling laws at smaller heliocentric dis- tances are discussed in Sect. 7.

# General solar wind model

Finally, we combine the obtained solar activity and distance dependencies for shifting the frequency distributions. The result is an empirical solar wind model for the inner heliosphere.

Under the assumption that the exponential fall-off laws do not change with time/solar activity (as shown above...), they can be used in general.

We combine the fit coefficients of the median relation for solar activity dependence (7) with the ones from the exponential distance dependence (previous section)

*x*med(*ssn*, *r*) = (*a*med · *ssn* + *b*med) · *re*, (11) to get the combined model function *W*,,,(*x*, *ssn*, *r*). And for

the velocity *W*I,I,,(*x*, *ssn*, *r*) with the double lognormal function

**Table 3.** Fit coefficients for the median and mean solar distance dependencies of the four parameters from the combined Helios data set. The errors in brackets are the estimated standard deviations of each fit parameter. The crossing distance is the point where the fitted median and mean intersect. The year variation is the weighted standard deviation from all yearly fitted exponents.

Median Mean Crossing distance Year variation

*d*med*a e*med *d*avg*a e*avg [au] ∆*e*

Parameter

Magnetic field 5.377(92) −1.655(17) 6.05(10) −1.546(18) 0.339(11) 3

0.11

Velocity 4.107(28) 0.058(13) 4.356(24) 0.049(10) 0.7(83) × 10

0.012

Density 5.61(27) −2.093(46) 7.57(30) −2.010(38) 0.027(73) 0.072

Temperature 7.14(23) −0.913(39) 9.67(21) −0.792(28) 0.082(85) 0.005

**Notes.** (*a*) Values in their respective units nT, 102 km s−1, cm−3 and 104 K.

figures/radial\_fit\_4\_thesis\_light\_skip\_pdfcairo\_plot.pdf

**Fig. 7.** Helios hourly data plots of the four solar wind parameters over solar distance. The mean and median per 0.01 au data bin and their fit curves are plotted as well. The Helios data has a native distance resolution of 0.01 au. To make the abundance visible in these plots, we added a random distance value of up to ±0.005 au.

**Table 4.** Fit coefficients from the single lognormal exponential function, respectively double lognormal for the velocity (combined Helios data). The errors in brackets are the estimated standard deviations of each fit parameter.

Parameter Median*a* Mean*a* Exponent Balance

*d*m, ed *d*a,vg *e*, *c*,

Magnetic field 5.358(25) 5.705(28) −1.662(11) –

Density 5.424(33) 6.845(47) −2.114(20) –

Temperature

,,

6.357(64) 10.72(14) −1.100(20) –

Velocity *W*1 3.707(13) 3.748(16) 0.0990(51) 0.557(45)

*W*2,,

*W*I,I,

5.26(13) 5.42(11)

4.13(13)*b* 4.47(11)*b* – –

**Notes.** (*a*) Values in their respective units nT, 102 km s−1, cm−3 and 104 K. (*b*) Velocity median and mean 1 au values for the resulting function. Error estimates derived from the individual fit part errors.

figures/mixed\_fit\_fixed\_4\_paper\_f\_plot.pdf

**Fig. 8.** Solar wind parameter’s frequency distributions over solar distance. Plotted are the binned Helios data and the exponential lognormal fit model (double lognormal for the velocity) with their median values (white).

(5).

empirical model limits (spherical coordinates):

sensus of the Solar Cycle 24 Prediction Panel5 (until end of 2019).

For the prediction of the next solar cycle 25 we simply as-

* heliocentric distance range 0.29–0.98 au
* rotational symmetry
* confined to ecliptic ( 7.2◦ HGI) model constrictions:

±

* solar distance dependency function
* frequency distribution functions
* neglected influence from heliolatitude variation

# Model extrapolation to PSP orbital time and position

To estimate the solar wind environment at PSP’s planned orbital positions during its mission time, SSN predictions are included into the general solar wind model and extrapolations to the PSP perihelion region are performed.

* 1. *SSN prediction for PSP mission time*

For the SSN short-term prediction are several sources available. The SIDC provides 12-month SSN forecasts4 obtained from dif- ferent methods (e.g. Kalman filter combined method). The Space

sume a course similar to the last and thus we shift the last cycle by 11 years. Additionally we consider the two alternatives of half and twice its amplitude. The SSN for PSP’s first perihelion will be small—certainly below 20, whereas its nearest perihelia, which commence at the height of cycle 25, will have as of now almost unpredictable SSN amplitudes (see Fig. 10).

* 1. *Near-Sun extrapolation for PSP orbit*

Parker Solar Probe is planned to launch in mid 2018. With its first Venus flyby it will swing into Venus’ orbital plane(?) (3.86◦ to Sun’s equator), which allows for additional seven flybys to finally reduce its perihelion distance to a minimum of less than 10 Rs (Fox et al. 2015) (Fig. 10).

For the extrapolation to PSP’s orbital range we just assume that our derived distance scaling laws do not change. The comparison with existing near-Sun models reveals that this is not entirely true (Fig. 11).

The magnetic field magnitude from our extrapolation is flat- ter than the analytical magnetic field model from Banaszkiewicz et al. (1998), who constructed a dipole plus quadrupole

Weather Prediction Center’s (SWPC) prediction follows a con-

5 <http://www.swpc.noaa.gov/products/>

4 <http://sidc.be/silso/forecasts>

solar-cycle-progression

figures/sw\_extrapolation\_ssn\_b\_plot.pdf

**Fig. 11.** Radial extrapolation of the solar wind parameters to the PSP orbit region. The from Helios and OMNI measurements obtained models are extrapolated to the PSP region—for the extreme cases of solar minimum (SSN = 0) and maximum (SSN = 200). Note that there is a time lag to the SSN depending on the solar wind parameter. The magnetic field radial dependence is slightly flatter than the analytic DQCS model for solar minimum which Banaszkiewicz et al. (1998) derived. Below 20 Rs the slow wind velocity is overestimated in comparison to the measurements from Wang et al. (2000)) and (Sheeley et al. 1997). They derived temperature and sonic point values for slow solar wind with the isothermal expansion model (Parker 1958). Down to PSP’s perihelion the density is in good agreement with the model from Leblanc et al. (1998). to 1-column...?

plus current sheet (DQCS) model. We attribute this effect to the from a lognormal shape deviating distribution (see Sect. 5.2).

Alfvénic critical surface i.e. source surface (see Fox before 2.1)

in direction to the Sun is at about 2.5 Rs the source surface (Schatten1969)

sonic and Alfvénic critical point positions (see Sittler & Guhathakurta (1999))

sonic point and slow solar wind origin (Sheeley et al. 1997) approaching these regions, acceleration plays a role

Wang et al. (2000), sources of slow solar wind + IMF regulation mechanism + blobs; compare with our slow V lognormal part; Parker solution

-> below 20 Rs PSP will fly well into sw acceleration region

Sheeley et al. (1997) -> LASCO coronagraph observed speed profile of coronal features tracing the slow solar wind, 2–30 Rs

* sonic point 5–6 Rs
* slow solar wind origin 3–4 Rs

The near-Sun (PSP perihelion) solar wind velocity is expected to be slower than our model’s estimates, because the

position of the source (Alfvénic critical) surface is predicted to lie between 15–30 Rs (Schatten1969, Sittler1999, Exarhos2000, Katsikas2010, Goelzer2014; choose references...), up to which the solar wind is believed to be accelerated.

The Parker (1958) model of an isothermal expanding corona with a temperature of 106 K and a critical radius of 5.8 Rs.

We expect that even our Sun-nearest extrapolated density at PSP perihelion agrees well with the actual, since Leblanc et al. (1998) derived an electron density model from type III radio

burst observations. Their model shows that the density distance dependency scales with *r*−2 and steepens not until below 10 Rs with *r*−6 (see Fig. 11).

magnetic field and temperature: crossing distance effect

* 1. *PSP solar wind environment estimation*

Implementing the orbital distance data and predicted SSN for the mission time we can derive PSP’s estimated solar wind environ- ment *W*,,,(*x*, *ssn*, *r*).

The zoom into the first and the nearest perihelia show which so- lar wind parameter magnitudes can be expected there (Figs. 12

figures/SPP\_orbit\_predicted\_SSN\_overview\_e\_plot.pdffigures/SPP\_perihelia\_prediction\_nearest\_e\_plot.pdf

**Fig. 10.** PSP’s solar distance during its mission time (top). Consec- utive Venus flybys bring its perihelia nearer to the Sun. Actual and predicted SSN (bottom), i.e. SIDC 13-month smoothed monthly actual SSN, SIDC prediction, SWPC prediction and simply by 11 years shifted SSN from previous cycle 24, together with two alternative trends of half and twice its amplitude.

figures/SPP\_perihelia\_prediction\_e\_plot.pdf

**Fig. 12.** Estimated solar wind parameter medians (black) and their error bands (grey) during 12 days in 2018 with PSP’s first perihelion at about

0.16 au. For the velocity the combined median is calculated and also the SSN independent slow and fast parts are plotted (dotted).

and 13).

* 1. *Model validity and error sources*

validity and estimation of error size outside of valid model range...

derive heliocentric distance depending error... list simplifications/approximations...

error estimation for general model and extreme value tendencies

**Fig. 13.** Estimated solar wind parameter medians (black) and their error bands (grey) during during 12 days in 2024 with PSP’s nearest perihe- lion at 0.0459 au. For the velocity the combined median is calculated and also the SSN independent slow and fast parts are plotted (dotted).

error sources:

* extrapolation
* lognormal model
* SSN variance

all estimates outside these boundaries are extrapolations with large uncertainties.

discuss high value zoom figures

The solar wind parameters vary with solar distance as well as with latitudinal separation from the heliospheric current sheet (HCS).

The OMNI data is time-shifted to the nose of the Earth’s bow shock. This leads to yearly solar distance variations of > 2 % (cite?) as the Earth orbits the Sun. Furthermore, its orbit within the ecliptic leads to a yearly variation of 7.2◦ in heliospheric latitude.

±

The HCS’s position in latitude is highly variable around the solar equator (Schwenn 1990, p. 127 ff.?).

Error estimation over the year (seasonal/monthly) -> we expect variations to be less than 5 %

# Results and discussion

list of results:

* empirical solar wind model for inner heliosphere within ecliptic
* low velocity at 0.0459 au
* slow/fast ratio SSN dependency
* application validity of lognormal distributions

–> B inversion of frequency distribution

—> magnetic field distribution’s with distance increasing high value tail -> source are compression regions (why with density no increase?); look into Parker1958’s B-field formula...

varying shape with distance is indicator for internal physical processes (mixing/turbulence...)

Balogh et al. (1999) p. 162 ff (origin and formation of CIRs in inner heliosphere with Helios data; latitude V dependence) Balogh2009 (HMF review + inner heliosheath)

Aschwanden2004, p. 29

individual velocity part discussion -> there is no specific velocity threshold between slow and fast solar wind types, the velocity ranges of both types overlap.

Not only the slowest wind but also the fastest wind is expected to converge to the average speed (Sanchez-Diaz2016 p. 2835, using MHD-model -> very slow solar wind is continuation of slow wind) (because of interaction).

The ratio of both varies with solar activity, e.g. 3 years after maximum, polar coronal holes are observed to often have equatorial extensions (cite?). see and use Bougeret et al. (1984) p. 498...

larger influx from higher latitudes (see figure b))

In most studies the density distance dependence is assumed to scale with *r*−2 (cites), assuming a constant velocity.

# Conclusions

Further investigations should be done into structure extrapola- tions; outward extension of model to Mars seems feasable...

Further questions:

nearer to the Sun (at and below the source surface) the solar wind expansion in the ecliptic should be less spherical but more circular due to the influx from higher latitudes. => density exponent > -2

see Li2011 Fig. 1

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