Photometry as a Proxy for Stellar Activity in Radial Velocity Analyses

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Abstract

Stellar activity remains a limiting factor in measuring precise planet parameters from radial velocity spectroscopy, not least in the search for Earth-mass planets orbiting in the habitable zones of Sun-like stars. One approach to mitigate stellar activity is to use combined analyses of both radial velocity and time-series photometry. We present an analysis of simultaneous disk-integrated photometry and radial velocity data of the Sun in order to determine the useful limits of a combined analysis. We find that simple periodogram or autocorrelation analysis of solar photometry give the correct rotation period <50% of the time. We therefore use a Gaussian process to investigate the time variability of solar photometry and to directly compare simultaneous photometry with radial velocity data. We find that the hyperparameter posteriors are relatively stable over 70 yr of solar photometry and the amplitude tracks the solar cycle. We observe good agreement between the hyperparameter posteriors for the simultaneous photometry and radial velocity data. Our primary conclusion is a recommendation to include an additional prior in Gaussian process fits to constrain the evolutionary timescale to be greater than the recurrence timescale (i.e., the rotation period) to recover more physically plausible and useful results. Our results indicate that such simultaneous monitoring may be a useful tool in enhancing the precision of radial velocity surveys.

Unified Astronomy Thesaurus concepts: Radial velocity (1332); Stellar activity (1580); Solar activity (1475)

1. Introduction

Transit surveys are detecting hundreds of Earth-sized planets and measuring their sizes and orbital properties. To understand the composition and potential habitability of these planets, mass measurements are needed to calculate a bulk density and interpret future atmospheric transmission spectroscopy measurements (Batalha et al. 2019). Furthermore, future high-contrast characterization of Earth-mass planets in the habitable zone of nearby stars would benefit from target identification by precise radial velocity surveys (Gaudi et al. 2020). These Earth-like planets orbiting in the habitable zones of G stars produce a radial velocity signal of only 10 cm s\(^{-1}\). Due to the high precision and long monitoring time needed, no true Earth analogues currently have mass measurements from the radial velocity method.

Radial velocity instrument stability and calibration is rapidly approaching the ability to detect an Earth-like signal. For example, the NEID spectrograph has an error budget of 27 cm s\(^{-1}\) (Halverson et al. 2016), the Echelle SPectrograph for Rocky Exoplanets and Stable Spectroscopic Observations (ESPRESSO) is achieving a 28 cm s\(^{-1}\) dispersion on sky over a single night (Pepe et al. 2014), and laser frequency comb measurements on EXtreme PREcision Spectrometer (EXPRES) are showing an instrumental precision of <10 cm s\(^{-1}\) (Zhao & The EXPRES Team 2019; Blackman et al. 2020; Petersburg et al. 2020). Yet there is much work needed to mitigate stellar activity to detect such a small signal on sky.

The High Accuracy Radial velocity Planet Searcher for the Northern hemisphere (HARPS-N) team have been collecting disk-integrated radial velocity observations of our Sun over the last four years (Collier Cameron et al. 2019). After accounting for the radial velocity shifts from all of the solar system planets and thoroughly vetting for data quality, there remains an underlying solar variability signal of 5 m s\(^{-1}\) with a daily rms scatter of <1 m s\(^{-1}\). Stellar activity therefore remains the largest “noise” component in radial velocity analyses of the Sun, and will likely limit future surveys unless this noise can be mitigated.

Stellar activity associated with a star’s rotation period can affect the analysis of orbiting planets or be mistaken as a planetary signal due to their overlapping time frames of days to tens of days (e.g., Robertson et al. 2014; Mortier & Collier Cameron 2017; Haywood et al. 2018). Starspots cause variations in stellar line profiles and centroids (e.g., Vogt et al. 1987); therefore monitoring stellar rotation with photometry may be a valuable tool for identifying and mitigating these stellar activity signals in radial velocity data. Previous works have found similar periodicities in photometry and radial velocity data and have used this correspondence to improve the precision of the planet parameters (e.g., Aigrain et al. 2012; Haywood et al. 2014; López-Morales et al. 2016; Kosiarek et al. 2019).

In this paper, we explore the relationship between Gaussian process parameters derived from solar photometry to those derived from solar radial velocity data in order to better understand how photometry can be used for activity mitigation. We describe the data used in this paper and look for common periodicities between the data sets in Section 2. We introduce Gaussian processes and our analysis methods in Section 3. We examine the time variability of solar photometry in Section 4.1, followed by a direct comparison between Gaussian process parameters derived from solar photometry and radial velocity data in Section 4.2 before concluding with advice for future observations in Section 5.

2. Solar Data Sets

The Sun makes a particularly good test case due to the abundance and precision of solar monitoring. In this work, we

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examine (1) the time variability of solar photometry over 70 yr of data and (2) the relationship between photometry and radial velocity data through comparing four years of simultaneous solar photometry and radial velocity data.

The HARPS-N team recently published a large solar radial velocity data set taken with a solar telescope that feeds disk-integrated sunlight to the HARPS-N spectrograph (Collier Cameron et al. 2019). The radial velocity data span nearly four years, from 2015 July to 2019 March (Figure 1). Dozens of data points are taken per day, weather permitting, with 5 minute integrations and result in a typical precision of 0.43 m s$^{-1}$.

The HARPS-N data reduction package also produces two line measurements alongside the radial velocity data, the FWHM of the cross-correlation function (CCF) and a measurement of the asymmetry of the CCF called the bisector inverse slope (BIS). These two measurements can be used as stellar activity indicators, therefore we will compare them alongside the radial velocity data throughout our analysis.

The SOlar Radiation and Climate Experiment (SORCE) measures the total solar irradiance (TSI) with the total irradiance monitor (Lawrence et al. 2000). The TSI data products\(^5\) include daily and 6 hr average irradiances normalized to a distance of 1 au and the data have a typical precision of 0.5 W m\(^{-2}\) (Figure 2).

The EMPirical Irradiance REconstruction (EMPIRE) is a solar irradiance model with the goal of providing uninterrupted and coherent TSI time series for climate modeling (Yeo et al. 2017). The solar irradiance is calculated by a linear combination of solar activity indices connected to sunspots and faculae. The data set begins 1947 February and extends to 2016 September (Figure 3). EMPIRE overlaps with the SORCE data set from 2003 to 2016 with good agreement (rms difference of 0.12 Wm\(^{-2}\)). Therefore, this work will use the EMPIRE data set when discussing variations over time due to its much longer baseline and the SORCE data set when comparing with the HARPS-N radial velocity data due to the overlap between these two data sets.

2.1. Initial Data Comparisons

To directly compare the EMPIRE and SORCE photometry with the HARPS-N radial velocity, we first split each of the data sets into year-long segments that overlap with the timescale of the HARPS-N data. These segments are labeled “Year 1–4” in Figures 1–3.

The three data sets used in this project have different sampling cadences and distribution. To normalize the inputs for each fit, we binned the data points in daily bins with uncertainties that represent the standard deviation of the points. This binning was also performed to focus on the solar rotation timescale, as opposed to short timescale activity such as p-modes and granulation. Binning on a daily cadence is also standard practice in many precise radial velocity analyses (Dumusque et al. 2011; Chaplin et al. 2019).

We initially looked for common periodicities in the data sets using two different techniques, a Lomb–Scargle periodogram and autocorrelation. The Lomb–Scargle periodogram results are shown in Figure 4. The majority of the peaks occur at the solar rotation period or at its harmonics. In all four years, the HARPS-N radial velocity data have peaks at the stellar rotation period (27 days) and the one-half and one-third harmonic. In two years, Year 1 and Year 4, the peak at one-half of the rotation period is the highest and the peak at the rotation period is the second highest. The HARPS-N FWHM and BIS data

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\(^5\) http://lasp.colorado.edu/home/sorce/data/tsi-data/
primarily follow the radial velocity data, except for Year 4 which has few significant peaks. For the photometry, the majority of the peaks occur at the stellar rotation period or its harmonics, however the peaks are less consistent than the HARPS-N radial velocity data.

Due to the stochastic nature of stellar activity, the highest peak in a periodogram is often not at the stellar rotation period (Boisse et al. 2011; Nava et al. 2020), therefore we also examine autocorrelation plots for all of our data sets. We first linearly interpolate the HARPS-N data to a uniform daily cadence to perform the autocorrelation using numpy.interp and numpy.correlate in Python. The autocorrelation for the photometry and radial velocity data over Years 1–4 are shown in Figure 5. The HARPS-N radial velocity autocorrelation has a distinct sawtooth pattern in Years 1, 2, and 4, with peaks at the stellar rotation period and multiples thereof. Year 3 has a break in the middle of the data set that likely creates the broad peak at 125 days and partially washes out the stellar rotation signal. The FWHM and BIS also peak at the solar rotation period and its harmonics in Years 1–3; there are no significant peaks in Year 4. The photometry follows the same sawtooth pattern in Years 1 and 4. Years 2 and 3 have larger variance in the amplitude of the total solar insolation which may contribute to the inconsistent peaks. In summary, there is good agreement between the SORCE, EMPIRE, and radial velocity data for Years 1 and 4, and good agreement between the radial velocity, FWHM, and BIS data for Years 1–3.

2.2. EMPIRE Data Periodicities

To further examine the accuracy of periodogram and autocorrelation analyses we perform both on each year of the 70 yr EMPIRE data set. We record the highest three peaks in
the periodogram and autocorrelation plots for each year to determine how often the top three peaks are consistent with the solar rotation period, shown as a histogram in Figure 6. In a periodogram, the solar rotation period is consistent with the highest peak 14.3% of the time and one of the highest three peaks 48.6% of the time. For the autocorrelation, the rotation period is consistent with the highest peak 21.4% of the time.

Figure 4. Periodogram comparison of the solar photometry and radial velocity data. All data sets are plotted with individual y-offsets for clarity. The stellar rotation period (27 days, thick gray line) and its harmonics (thin gray lines) are plotted for comparison. We find that many of the peaks in all data sets line up with the solar rotation period and its harmonics.

Figure 5. Autocorrelation comparison of the solar photometry and radial velocity data sets. The photometry (SORCE and EMPIRE) and line indicators (HARPS-N FWHM and HARPS-N BIS) are normalized to the scale of the HARPS-N radial velocities and are plotted with a y-offset for clarity. The stellar rotation period (27 days, thick gray line) and its harmonics (thin gray lines) are plotted for comparison. Many of the peaks in both data sets line up with the stellar rotation period and its harmonics.
and one of the highest three peaks 44.3% of the time. As the highest peaks are often at other values unrelated to the solar rotation period, one should exercise caution when using either of these methods to determine a stellar rotation period.

### 3. Methods

#### 3.1. Introduction to Gaussian Processes

In this paper we investigate the validity of using photometry to constrain the hyperparameter values in a Gaussian process analysis using solar data as a test case.

Gaussian processes are a statistical method for modeling correlated noise. Gaussian process regression allows us to determine posterior distributions with uncertainties that are typically used for fitting radial velocity data with Keplerian orbits. We use a subset of this package to fit only a Gaussian Process to the data. RadVel first performs a maximum-likelihood fit to the data and then determines errors through a Markov Chain Monte Carlo analysis. We used 50 walkers, 2,500,000 steps, and a Gelman–Rubin statistic of 1.01 for convergence; the rest of the parameters are set to the default values as described in Fulton et al. (2018).

#### 3.2. Fitting a Gaussian Process

We model each of our solar data sets using a quasi-periodic Gaussian process with a covariance kernel of the form

$$k(t, t') = \eta_1^2 \exp\left[-\frac{(t - t')^2}{\eta_2^2} - \frac{\sin^2\left(\frac{\pi(t - t')}{\eta_3}\right)}{\eta_4^2}\right],$$  

where the hyperparameter $\eta_1$ is the amplitude of the covariance function, $\eta_2$ is the active region evolutionary timescale, $\eta_3$ is the period of the correlated signal or recurrence timescale, and $\eta_4$ is the length scale of the periodic component. This kernel allows for active region evolution through the decay term and a periodic component such as stellar rotation; therefore, it is a suitable kernel choice for fitting stellar activity (e.g., Haywood et al. 2014; Kosiarek et al. 2019).

We implement the Gaussian process fit using RadVel\(^6\) (Fulton et al. 2018). RadVel is an open source Python package that is typically used for fitting radial velocity data with Keplerian orbits. We use a subset of this package to fit only a Gaussian Process to the data. RadVel first performs a maximum-likelihood fit to the data and then determines errors through a Markov Chain Monte Carlo analysis. We used 50 walkers, 2,500,000 steps, and a Gelman–Rubin statistic of 1.01 for convergence; the rest of the parameters are set to the default values as described in Fulton et al. (2018).

### 4. Results

#### 4.1. Solar Temporal Variations using EMPIRE

To examine the time variation of the solar insolation and its Gaussian process hyperparameters, we perform a Gaussian process fit using a quasi-periodic kernel on each year of data separately. An example fit for one year of EMPIRE data is shown in Figure 7. A year was chosen as the timescale so that sufficient rotation periods would occur in each group to accurately determine the parameters from the Gaussian process fit while still being short enough to be a plausible baseline for stellar photometry observations. We acknowledge one of the limitations with this method is that we are monitoring discrete active regions, and a degree of smoothness (e.g., Angus et al. 2018). In some cases, radial velocity data are independently able to constrain both the stellar activity and planet parameters (Faria et al. 2016; Damasso & Del Sordo 2017). However, radial velocity data are often too sparse to well constrain Gaussian process hyperparameters in addition to all of the planet parameters. Therefore, other data sources are used to constrain the hyperparameters and incorporated into the radial velocity analysis as priors (e.g., Haywood et al. 2014; Rajpaul et al. 2015; Kosiarek et al. 2019).

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\(^6\) RadVel is available at https://github.com/California-Planet-Search/radvel.
the evolutionary timescale on the lower end to avoid overfitting and the higher end as the model would be unable to detect a timescale longer than the data baseline (uniform prior of 5 days $< \eta_2 < 365$ days). For the recurrence timescale, we also limit the lower end to prevent overfitting and upper end at the baseline (uniform prior of 5 days $< \eta_3 < 365$ days). For other stars, the recurrence timescale can be constrained by a $v \sin(i)$ measurement as short rotation periods produce large amplitudes or through determining the stellar rotation period through other methods. Lastly, we constrain the length scale of the periodic component (Gaussian prior of $\eta_4 = 0.5 \pm 0.05$). The length scale is related to the average number of minima in a sample drawn from the Gaussian Process prior. An $\eta_4$ value of 0.5 means that there are on average two to three minima. Jeffers & Keller (2009) finds that a random distribution of several active regions on the surface of a star produces two minima in the light curve, resulting in the Gaussian prior around 0.5 used in previous Gaussian process fits (e.g., Haywood et al. 2014; López-Morales et al. 2016).

The posteriors of the four hyperparameters from 1947 to 2016 are shown in Figure 8. The amplitude shows a clear 11 yr variation matching the 11 yr solar magnetic activity cycle. The variations also correlate well with the number of sunspots and inversely with the cosmic ray flux (Usoskin 2013).

The evolutionary timescale and recurrence timescale are interrelated. In years with an inferred low evolutionary timescale, the recurrence timescale is fairly unconstrained as the model is able to well fit the data without a strong periodic component. The recurrence timescale describes the periodic component of the photometry and therefore should relate to the solar rotation period. The recurrence timescale posterior is well constrained at the solar rotation period for only a few years (1982, 1983, 1986, 1994, 2008, 2009, and 2011). These years all have something in common: the evolutionary timescale is longer than the recurrence timescale. For the majority of the other years, the inferred evolutionary timescale is shorter than the inferred rotation period. From this, it appears that the model is only successful in determining the rotation period if the evolutionary timescale is longer than the recurrence timescale.

On the Sun, sunspot lifetime is proportional to the spot area (Gnevyshev 1938; Waldmeier 1955). Measured sunspot lifetimes range from a few days (Petrovay & van Driel-Gesztelyi 1997) to hundreds of days (Henwood et al. 2010). However, the evolutionary timescale is not describing individual spot lifetimes but instead the evolution of large active regions. Measured lifetimes of solar active regions range from hours to months (Schrijver & Zwaan 2000; van Driel-Gesztelyi & Green 2015); the lifetime is roughly proportional to the active region’s peak magnetic flux and can depend on the phase of the solar magnetic cycle and strength of surrounding magnetic fields. Large active regions last from weeks to months, many of which have a longer lifetime than the solar rotation period, providing physical justification for a prior restricting the evolutionary timescale to be longer than the recurrence timescale.

Furthermore, the timescales of active region evolution were estimated for 35 main-sequence FGK stars through $S$-index measurements at Mount Wilson Observatory (Donahue et al. 1997). The estimated lifetimes of these active regions ranged from 75 to 3000 days and the stellar rotation period ranged from 5 to 200 days with an average near 50 days. All of these stars have longer active region evolution timescales than their measured rotation periods, suggesting that this relationship holds for other FGK dwarf stars.

This relationship motivates our second fit where we include an additional prior to constrain the evolutionary timescale to be larger than the recurrence timescale ($\eta_2 > \eta_1$). With this additional prior, the recurrence timescale is consistent with the solar rotation period to 1$\sigma$ for 48 of the 70 yr. In addition, many of the previously multi-modal posteriors are now single peaks and the long tail posteriors are better constrained. If one is using a Gaussian process to determine a stellar rotation...
period, we recommend including this prior. The amplitude shows a small systematic increase with the additional prior; the trend with the solar magnetic cycle remains strong. The structure parameter has a greater variation between the years and has a lower average (approximately 0.4), favoring a more high-frequency structure in the light curves.

4.2. Direct Comparison of Photometry with Radial Velocity Data

Radial velocity data is often sparsely sampled and therefore poorly constrains the Gaussian process hyperparameters without additional information. In previous works, active stellar lines or photometry have been used to provide stellar activity information for the radial velocity fit (e.g., Aigrain et al. 2012; Haywood et al. 2014; Kosiarek et al. 2019). A key assumption in these analyses is that stellar activity is recorded in the same way between the two data types; however, for stars with low magnetic activity the radial velocity data may be dominated by phenomena not observable from a light curve (Wright 2005; Tayar et al. 2019). The overlap between the SORCE photometry data set with the well-sampled HARPS-N radial velocity data set provides an unique opportunity to test this assumption for Sun-like stars.

The same procedure described above for the EMPIRE analysis (Section 4.1) is performed here, and the results are shown in Figure 9. To recap, two fits are run for each data set; the first (posteriors shown as a black outline) with the following two uniform priors: 5 days < \( \eta_2 < 365 \) days, 5 days < \( \eta_3 < 365 \) days and one Gaussian prior: \( \eta_4 = 0.5 \pm 0.05 \). The second (posteriors shown as a solid color interior) has an additional prior constraining the decay timescale to be larger than the recurrence timescale (\( \eta_2 > \eta_3 \)).

The main takeaway from these fits is that the posteriors are largely consistent between all data sets in the Gaussian process fit with the additional prior (\( \eta_2 > \eta_3 \)); therefore, photometry can provide valuable information about stellar activity for radial velocity analyses. In both fits, the amplitude posteriors are largely consistent within each data set with a slight downward trend as the data approaches the solar minimum.

There are two interesting comparisons from the initial fit without the additional prior. First, the SORCE photometry and HARPS-N radial velocities have consistent posteriors that match the solar rotation period only in Year 4, where the SORCE data has a longer evolutionary timescale than recurrence timescale. Second, the FWHM and BIS show opposite results to the photometry. The FWHM data well matches the radial velocities for Year 1–3 and not Year 4. The BIS posteriors for Year 1–3 are consistent with the solar rotation period and has a longer evolutionary timescale than recurrence timescale.

The posteriors of the second analysis display much higher agreement between the different data sets. The SORCE photometry and HARPS-N radial velocities are consistent for three of the four years; the inconsistent year, Year 2, SORCE instead has a recurrence timescale of half of the solar rotation period. The radial velocities and FWHM posteriors are now both well constrained and the recurrence timescale matches the solar rotation for Years 1–3. The BIS remains unchanged for Years 1–3 as the evolutionary timescale was already longer.

Figure 8. Gaussian process hyperparameter posteriors for individual fits of each year of EMPIRE photometry, with (blue shaded) and without (black outline) a prior restricting the evolutionary timescale to be larger than the recurrence timescale. This added prior results in a good match between the solar rotation period and the recurrence timescale posterior.
than the recurrence timescale and the recurrence timescale matched the solar rotation period. Lastly, \( \eta_4 \) may be under-constrained in the three HARPS-N data sets as the posteriors closely resemble the Gaussian prior on \( \eta_4 \). The length scale parameter for the SORCE photometry is around 0.4, lower than the length scale parameter for the three HARPS-N data sets, consistent with the length scales found in the EMPIRE analysis (Section 4.1).

Year 4 is distinct as the FWHM and BIS do not have well-constrained posteriors and do not match the photometry or radial velocities. Additionally, Year 4 is near the solar minimum and is the one year that the SORCE photometry matched the HARPS-N radial velocities without the additional prior; perhaps solar activity displays different characteristics in line measurements compared to photometry throughout the solar cycle. Further high-cadence radial velocity monitoring of the Sun will be important to confirm many of the observations from this paper and potentially detect changes as a function of the solar cycle.

5. Conclusion

We analyzed simultaneous disk-integrated photometry and radial velocity data of the Sun in order to determine the useful limits of a combined analysis. We examined the periodicities of five simultaneous data sets, SORCE and EMPIRE photometry, HARPS-N radial velocity, and two HARPS-N line indicators: FWHM and BIS. The periodograms and autocorrelation plots often displayed power at the stellar rotation period and its harmonics; however, the stellar rotation period was not always the highest peak. In the 70 yr EMPIRE data set, the highest peak matched the solar rotation period 14.3% and 21.4% of the time for our periodogram and autocorrelation analysis respectively. We recommend exercising caution when using either of these methods to determine a stellar rotation period due to the large number of peaks at times unrelated to the solar rotation period.

A Gaussian process analysis of photometry can provide more reliable estimates of a star’s rotation period. We used a Gaussian process to investigate the time variability of solar photometry through analyzing 70 yr of EMPIRE data. The time variability analysis determined that the Gaussian process amplitude hyperparameter followed the 11 year solar magnetic cycle. The evolutionary timescale and recurrence timescales remained relatively stable throughout and the recurrence timescale matched the solar rotation period when the additional prior constraining the evolutionary timescale to be greater than the recurrence timescale was included. Therefore, this Gaussian process analysis identified the correct solar rotation period more often than either the periodogram or autocorrelation analyses.

Photometry can also be a valuable tool for understanding stellar activity in radial velocity data fits. In our direct comparisons between the Gaussian process hyperparameters
of the SORCE photometry, HARPS-N radial velocity data, and HARPS-N FWHM and BIS line measurements, the evolutionary timescale and recurrence timescale were consistent between the data sets after including the same additional prior restricting the evolutionary timescale to be longer than the recurrence timescale. We recommend including this additional prior to improve the agreement between Gaussian Process hyperparameters derived from photometry and radial velocity data. The length scale parameter was consistent between the four data sets, although the value for the photometry data was systematically low compared to the other three.

Precision radial velocity surveys are aiming to characterize Earth-like planets around solar-type stars with cm s\(^{-1}\) radial velocity signals. Overlapping data spanning a full solar cycle or a few solar cycles is necessary to confirm the findings in this paper and to look for evidence for changes as a function of the solar cycle. Further work is also needed to determine how these conclusions could be applied to other stellar types.

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Facilities: SORCE, TNG.
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