CAN A NANOFLARE MODEL OF EXTREME-ULTRAVIOLET IRRADIANCES DESCRIBE THE HEATING OF THE SOLAR CORONA?

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ABSTRACT

Nanoflares, the basic units of impulsive energy release, may produce much of the solar background emission. Extrapolation of the energy frequency distribution of observed microflares, which follows a power law to lower energies, can give an estimation of the importance of nanoflares for heating the solar corona. If the power-law index is greater than 2, then the nanoflare contribution is dominant. We model a time series of extreme-ultraviolet emission radiance as random flares with a power-law exponent of the flare event distribution. The model is based on three key parameters: the flare rate, the flare duration, and the power-law exponent of the flare intensity frequency distribution. We use this model to simulate emission line radiance detected in 171 Å, observed by Solar Terrestrial Relation Observatory/Extreme-Ultraviolet Imager and Solar Dynamics Observatory/Atmospheric Imaging Assembly. The observed light curves are matched with simulated light curves using an Artificial Neural Network, and the parameter values are determined across the active region, quiet Sun, and coronal hole. The damping rate of nanoflares is compared with the radiative losses cooling time. The effect of background emission, data cadence, and network sensitivity on the key parameters of the model is studied. Most of the observed light curves have a power-law exponent, $\alpha$, greater than the critical value 2. At these sites, nanoflare heating could be significant.

Key words: Sun: corona – Sun: flares – Sun: UV radiation

Online-only material: color figures

1. INTRODUCTION

The mechanism of forming nanoflares is the dissipation of current sheets that arise from tangential discontinuities in the continuously evolving corona (Levine 1974; Parker 1988). Parker presumes that the change in the magnetic field across the current sheet, $\Delta B$, is critical for onset. When the strength $|\Delta B|$ of the discontinuity exceeds some threshold, there is a runaway dynamical instability leading to an explosive reconnection phase. This is similar to the sand pile model that has been used to explain the comparison that is also made between results of different methods. Avalanches of magnetic reconnection (Lu & Hamilton 1991) show that the magnetic field of the corona is in a state of self-organized criticality. To determine whether or not nanoflares are the main source of heat input to the corona, it is necessary to measure the energy frequency distribution of the smallest observed flares.

Hudson (1991) pointed out that the flare occurrence follows a power-law distribution, such as $dN \sim E^{-\alpha}dE$, in which $dN$ is the number of flares per energy interval $E$ and $E+dE$ (Lu & Hamilton 1991 obtained this distribution for complex systems that are in a self-organized critical state). The power-law index, $\alpha$, is a critical value for determining whether more weight is given to small-scale events (nanoflares) or larger ones (flares). Determination of the power-law index of the flare frequency distribution is a scientific challenge. Many authors have attempted to find this index. Benz & Krucker (1998), using Yohkoh and the Solar and Heliospheric Observatory (SOHO), have shown that the power-law index at the microflare frequency distribution is 2.5. Parnell & Jupp (2000) used Transition Region and Coronal Explorer (TRACE) observations and concluded that the energy of nanoflares is insufficient to heat the quiet-Sun corona. Aschwanden & Parnell (2002) obtained some other power-law distribution by combining the scaling law and fractal geometry for different observations. Aschwanden & Charbonneau (2002) gathered statistics of solar flares, microflares, and nanoflares and concluded that the power-law index falls below the critical value. An extended review on the simulation and observational results is given by Klimchuk (2006) and Klimchuk et al. (2009).

To determine the contribution of small-scale events (nanoflares) on the solar coronal heating, some applicable models have been investigated (e.g., Vekstein & Katsukawa 2000; Sakamoto et al. 2009; Terzo et al. 2011). Here, we use a model to simulate the observed extreme-ultraviolet (EUV) emitted radiation from Solar Terrestrial Relation Observatory (STEREO) and Solar Dynamics Observatory (SDO) that has been applied successfully to the UV radiance fluctuation in the quiet Sun (Pauluhn & Solanki 2007) and later to Solar Ultraviolet Measurement of Emitted Radiation (SUMER) observations of the corona in an active region (Bazarghan et al. 2008).

This paper is organized as follows. STEREO/Extreme-Ultraviolet Imager (EUVI) and SDO/Atmospheric Imaging Assembly (AIA) data analyses are described in Section 2. The nanoflare model is treated in Section 3. A type of Artificial Neural Networks (ANNs; Probabilistic Neural Network, PNN) is briefly discussed in Section 4. In Sections 5 and 6, the method and results are presented. The conclusions are given in Section 7.

2. STEREO/EUVI AND SDO/AIA DATA ANALYSIS

STEREO is the mission in NASA’s Solar Terrestrial Probes program that was launched in 2006 October and probes solar active phenomena and dynamics. It contains two identical observatories, one ahead of (A) and the other behind (B) the orbit of the Earth. Imaging the same events from two different locations enables us to have three-dimensional images (http://stereo.gsfc.nasa.gov/).

The EUVI telescope is part of the SECCHI instrument suite that is sensitive at 171 Å, 195 Å, 284 Å, and 304 Å. In the present...
work, we restrict ourselves to 171 Å images with time cadence of 2.5 minutes (Wülser et al. 2004). The spatial pixel size of both A and B images is 1.6 arcsec.

The SDO is designed to simultaneously study the solar atmosphere at small scales of space and time and in many wavelengths (http://sdo.gsfc.nasa.gov/mission/instruments.php). It was launched on 2010 February 11.

The SDO/AIA provides full-disk imaging of the Sun in several UV and EUV bands with a pixel size of about 0.5 arcsec and a cadence of 10 s.

Here, we take (1) a STEREO/EUVI 171 Å data set that has been recorded on 2007 June 13 with a cadence of 2.5 minutes and (2) an SDO/AIA 171 Å data set that has been recorded on 2010 August 22 with a cadence of 90 s.

The following steps are taken for data analysis.

1. Calibration of the recorded images using secchi_prep.pro on Solar Soft for EUVI data. The AIA level 1.5 data in the series aia_test.synoptic2 are used. These are binned data with a pixel size of 2 arcsec and a cadence of 90 s.
2. To remove the solar differential rotation we use the Solar Soft routine derot_map.pro.
3. EUVI and AIA provide full disk images. We select three regions as shown in Figure 1 for EUVI data and two regions for the AIA data. We attempted to select regions that cover active regions, quiet Sun, and coronal hole. Consider the first selected region of EUVI images. We partitioned it into smaller 3 × 3 pixel regions. Averaging on intensities of these smaller regions for 573 success images, we obtain a light curve. The same process was followed for other small remaining areas of the selected region. In a similar manner, other light curves were also obtained while partitioning the selected region into 5 × 5 and 9 × 9 pixel regions. The above process was followed for other selected regions (on EUVI and AIA), too. We note that the light curves have 573 and 939 time steps for EUVI and AIA, respectively. We fed each light curve (observed time series) to the network to determine the nanoflare model parameters (Section 6).

3. NANOFLAKE MODEL

Assuming that the coronal EUV emission is caused by many random flares with flare radiance, following a power-law frequency distribution we use a model that consists of a time series of random kicks according to the assumption that flaring is intrinsically a stochastic process. This model has five free parameters: the maximum and minimum flare amplitude, $y_{\text{max}}$ and $y_{\text{min}}$, the power-law exponent, $\alpha$, the damping time, $\tau_d$, and the flare rate, $p_f$. These are sufficient to produce our simulated EUV emission light curves.

Pauluhn & Solanki (2007) have shown that for a large number of independent random flares, the distribution of normalized radiance in the quiet Sun follows a lognormal. The same is true for active regions as pointed out by Safari et al. (2007) and Bazarghan et al. (2008).

In the following, we focus on the distributions of three selected regions shown in Figure 1. The intensity distributions and the lognormal fits are shown in Figure 2. The lognormal function is given by

$$f(x, \mu, \sigma) = \frac{1}{x \sqrt{\pi} \sigma} \exp \left( - \frac{\log(x - \mu)^2}{2 \sigma^2} \right),$$

where $x$, $\mu$, and $\sigma$ are the radiance, scale parameter, and shape parameter, respectively.

The good fits give us confidence in applying a stochastic flare model. The key parameters (power-law exponents, damping rates, and flare rates) of small-scale events (small eruptions) are not identifiable directly from observations. Pauluhn & Solanki (2007) and Safari et al. (2007) estimated that the damping rates and flare rates could be deduced by comparing light curves with simulated time series. They have used the shape parameters of lognormal fits and wavelet analysis.

It is interesting to compare our model and its parameters to those represented in recent works. Vekstein & Katsukawa (2000) assume that the energy distribution of the nanoflares has a power-law spectrum, bounded between some minimum and maximum energy release. They suggest that each nanoflare creates a filament with a cross-section area that is then divided into small grids. Nanoflares are generated randomly inside these grids with a finite occurrence rate and evolve with two stages of the cooling process (conduction and radiation heat).

The heat conduction and radiation are derived according to the scaling law (e.g., Rosner et al. 1978; Cargill 1993; Cargill & Klimchuk 1997). Sakamoto et al. (2009) have added the pressure balance (between the internal gas and external magnetic field of elemental filaments) to this model and analyzed the soft X-ray telescope (SXT) and TRACE intensities and intensity fluctuations. Terzo et al. (2011) introduce a constant heating as intrinsically flat light curves and imposed the Poisson noise to simulate the light curves. They concluded that...
the noises could not simulate the light curves observed by Hinode/SXT. Performing a Monte Carlo simulation, they perturb the flat light curves with a sequence of random segments of exponential decays linked together. The parameters of their model are the e-folding time, the interval between two successive perturbations, and the amplitude. Finally, they found some simulated light curves best match with the observed data.

One may ask what happens to the shape of the time series if the key parameters change. The light curves for flare models with different $\alpha$, $p_f$, and $\tau_d$ parameters are shown (Bazarghan et al. 2008, Figure 4). There is a physical picture of how the parameters affect the light curves. The mean, variance, skewness, and kurtosis of the time series are shown in Figures 3 and 4 versus $\alpha$. Both the mean and variance of the time series decrease as $\alpha$ increases. Expectedly, the higher the $\alpha$ (corresponds to smaller events) the lower the intensities become. With a $\alpha$ and $p_f$ fixed as $\tau_d$ increases, the mean and variance increase accordingly. This also occurs when $\alpha$ and $\tau_d$ are fixed and $p_f$ changes. The higher moments (skewness and kurtosis) of the time series increase with increasing $\alpha$, $\tau_d$, and $p_f$. Due to the lognormal shape of the distributions, both skewness and kurtosis values are positive (Figure 5). A positive value of skewness signifies a distribution with an asymmetric tail extending out toward larger radiance. In general, the geometric median (exp($\mu$)) is less than the geometric mean (exp($\mu+\sigma^2/2$)). This agrees with Terzo et al. (2011). They have shown that the distributions of intensity fluctuations taken from individual
pixels, multi-pixel subregions, or the entire active region as observed by Hinode/SXT are asymmetric.

We knew that the shape parameter is inversely in proportion to $\sqrt{\tau \rho_f}$ (Pauluhn & Solanki 2007) and that the lognormal shape parameter, $\sigma$, changes slightly with $\alpha$. Although the sharpness of the distribution indicates that for a higher $\alpha$, the distribution shape tends to be sharper as illustrated by the kurtosis increase (Figure 5).

Bazarghan et al. (2008) used ANNs to compare SUMER/SOHO observational time series with simulated time series. In this paper, a similar method is employed to determine the three key parameters of SECCHI/EUVI and SDO/AIA.
time series. The main advantage of the ANN method is that it enables us to obtain quantitative values for all parameters including $\alpha$, which Safari et al. (2007) had problems in analysis.

4. PROBABILISTIC NEURAL NETWORK

We employed a type of ANN, called PNN (Specht 1988, 1990), which is suitable for classification. A classification problem is defined with a set of inputs $P$ and targets $T$. PNN is a type of supervised network, which means that the learning process of the network takes place with an initially specified set of inputs and targets, called trained samples. If we assume that the input vectors contain $k$ different classes, then every target vector would contain $k$ elements. One of them is 1, which corresponds to its own class, and the others are 0. The PNN has two layers (Figure 6). When an input vector is fed to the network, the first layer calculates the distance between the input vector and the trained samples. So, it provides a vector for the elements that define the distance between the input and trained samples. The second layer produces a vector, which contains the probabilities using the output of the first layer. Finally, the competitive transfer function of the second layer chooses the maximum likelihood value within the probabilities vector and produces 1 for it and the output 0 for the others. Using this process, the network matches the input vector to one of the existent $k$ classes, which has the maximum likelihood value.

We ran the commands of the mentioned process in the Neural Network Toolbox (Wasserman 1993).

5. METHODS

We employed the following steps.

1. We ran the simulation code to generate light curves. The power-law exponent ranges between 1.4 $\leq \alpha \leq$ 4.4 in steps of 0.1, the duration time ranges between 2 $\leq \tau_d \leq$ 80 in steps of 1, and the flare rate falls between 0.1 $\leq p_f < 1$ in steps of 0.1. A total of 22,041 light curves for each combination of $\alpha$, $\tau_d$, and $p_f$ are obtained. For series with labels 1 and 7800, the set had ($\alpha = 1.4$, $\tau_d = 2$, $p_f = 0.1$) and ($\alpha = 2.4$, $\tau_d = 8$, $p_f = 0.6$), respectively. The larger the label’s value is, the greater the value of the power-law index becomes.

2. We fed the simulated light curves (as produced in previous steps) to the network. The network was tested to see whether it had been well trained. A set of simulated light curves (trained samples) was selected (manually) to feed the network to enable it to recognize and classify. If the network was able to recognize them, then it would be trained. Since our model has been based on a random number, we reproduced some light curves and fed them to the network for more accurate testing. We note that because the network uses a special function, the training error of the network is zero.

3. The input weights of the first layer of the network are a matrix, elements of which are the trained sample couples (input and targets). Let us consider an observed light curve the set of key parameters of which are not known. Once the unknown light curve (test sample) is fed to the network as an input vector, its distance from the 22,041 trained vectors is calculated by the first layer. So, it would be determined how close the input is to the vector of a trained set. Consequently, for an input vector closest to a trained one, the existent transfer function of the first layer produces 1. If the input vector has the same distance from two or more trained samples, then the output includes two or more 1’s. The second layer weights are set to a matrix, elements of which are the target vectors. Each vector only has a 1 in the row associated with that particular class of input, and 0’s elsewhere. The output of the first layer is multiplied by the matrix (target) and the product will be sent to the transfer function of the second layer which produces 1 for the greatest existent value and 0’s elsewhere. Using these processes, the network corresponds the input vector to one of the 22,041 existent classes because that class has the maximum probability of being correct. The output of the classifier includes a number that labels each class and corresponds to a set of key parameters. Now, the total observed light curves are fed to the classifier (network) as the test data set.

6. RESULTS

6.1. Results for STEREO/EUVI

For each of the three selected regions (300 $\times$ 300 pixels area) as marked in Figure 1, the light curves for average intensities were made. This gives a set of 10,000 light curves while averaging the intensities of the smaller $3 \times 3$ pixel regions, 3600 light curves while averaging the intensities of the smaller $5 \times 5$ pixel regions, and 1089 light curves while the selected
smaller regions are found to be $9 \times 9$ pixels. These light curves were fed to the network. The network labeled each light curve with a set of individual key parameters that corresponds to a simulated light curve. The output result of the network is shown in Figures 7–10.

In Figure 7, the observed light curves are compared with their matched simulated light curves found by the network. We see that the background radiance of the simulated light curves are remarkably close to the observed ones, which was a problem in previous studies of SUMER data (Bazarghan et al. 2008; see Figures 6 therein). As we can see, the observed light curves are noisier than the simulated one. One may wonder what would be the effect of the light curves’ noise on the network’s output? Using wavelet automatic de-noising (with different threshold and standard deviations), the noise of observed light curves is removed. In this case, the network’s output did not change.

The frequency of the observed light curves (tested samples) versus simulated light curves (trained samples) is shown in the upper panels of Figures 8–10. To do this, the histogram of output labels is calculated. We found that these labels ranged from 1 to 22,041, which corresponded to simulated light curves for which the key parameters range from the set of $(\alpha = 1.4, \tau_d = 2, \rho_f = 0.1)$ to $(\alpha = 4.4, \tau_d = 80, \rho_f = 0.9)$, as was stated in the previous section. In the bottom panels, the

**Figure 7.** Left panel: the simulated light curves for the three sets of key parameters are shown as legends with $\tau_r/\tau_d = 3$ and $y_{\max}/y_{\min} = 100$. Right panel: the observed light curves from EUVI 171 Å for the first selected regions while averaging the intensities of the smaller regions ($3 \times 3, 5 \times 5$, and $9 \times 9$ pixels from top to bottom, respectively). Both left and right are comparable to each other using the Artificial Neural Network.

**Figure 8.** Top panel: the frequency (histogram) of output labels (simulated light curve labels) for the observed light curves (first region of STEREO/EUVI image) constructed by averaging the intensities of the smaller region ($3 \times 3$ pixels). Bottom panel (from left to right): the histograms of $\alpha$, $\tau_d$, and $\rho_f$, respectively.
frequencies (histogram) of the power-law index, damping time, and flare rate are extracted as well. As we see in Figures 8–10 the network’s output for \( \alpha \) is concentrated in the range between 2 and 3. The mean power-law index, \( \alpha \), is 2.8, 2.7, and 2.6 for intensity averaged over 3 \( \times \) 3, 5 \( \times \) 5, and 9 \( \times \) 9 pixels, respectively. These are the similar values for the standard deviations, \( \sigma \approx 0.7 \). As was expected, the power-law index falls as the dimension of the pixel’s average intensity increases. This confirms that larger areas involve larger flare events. We note that the \( \tau_d \) values increase with binning. For example, the average \( \tau_d \) for 3 \( \times \) 3 pixels is 43 and for 9 \( \times \) 9 pixels is 53. The \( \tau_d \) seems to depend on the event size. This suggests that the larger areas have greater background, as expected.

The response of the \( \text{STEREO/EUVI} \ 171\,\text{Å} \) as a function of plasma temperature is within the range \( \log T_e \approx 5.1–6.7 \).
Figure 11. Top panel: the frequency (histogram) of output labels (simulated light curve labels) for the observed light curves (inside of the coronal hole of the SDO/AIA image) constructed by averaging the intensities of the smaller region (3 × 3 pixels). Bottom panel (from left to right): the histograms of $\alpha$, $\tau_d$, and $p_f$, respectively.

Figure 12. Top panel: the frequency (histogram) of output labels (simulated light curve labels) for the observed light curves (outside of the coronal hole of the SDO/AIA image) constructed by averaging the intensities of the smaller region (3 × 3 pixels). Bottom panel (from left to right): the histograms of $\alpha$, $\tau_d$, and $p_f$, respectively.

(Wüls et al. 2004). If we suppose the plasma cooling through this narrowband filter is dominated by radiative loss processes, then the cooling time, $\tau_{cool} \approx \tau_{rad}$, would range from a few seconds to an hour (see, e.g., Aschwanden 2004; Aschwanden et al. 2000). Using the mean dimensionless $\tau_d = 43$ and multiplying it by a cadence of 2.5 minutes (for STEREO/EUVI, 2007 June 13), we obtain a value of 2 hr. This is in good agreement with previous results (Aschwanden 2004).

Similar results are obtained for the other two selected regions. For clarification of background effects, we refer to the SDO/AIA data in the following section.

6.2. Results for SDO/AIA

To explain the background effect on the three key parameters, $\alpha$, $\tau_d$, and $p_f$, we used SDO/AIA 171 Å data sets taken on 2010...
August 22. To do this, a region from inside and outside a coronal hole were selected (Figure 1, right panel). The time series with an average intensity of $3 \times 3$ pixels were constructed and fed to the network.

The outputs of the classifier network are shown in Figures 11 and 12. The average $\alpha$ for both regions are the same value (i.e., 2.7). We see that more than 73% of $\alpha$ with $\pm 1\sigma_\alpha$ (standard deviation $\sigma_\alpha = 0.70$) falls in the mean value. The average $\tau_d$ is 48 and 52 for inside and outside the coronal hole, respectively. There are 62% and 64% of $\tau_d$ with $\pm 1\sigma_\tau_d$ ($\approx 17$) concentrated around mean values. This suggests that the background emission in the coronal hole is lower compared to its surrounding areas.

One point is that there is no considerable difference between $\tau_d$ inside and outside the coronal hole. This is due to the fact that the damping times should be roughly the same everywhere, because by choosing a specific filter, we are picking up the same event phase. The average $p_f$ is 0.4 and 0.5 for inside and outside, respectively. Actually, more than 53% and 59% of $p_f$ with $\pm 1\sigma_p$ ($\approx 0.2$) are concentrated around the mean values.

In the coronal hole, the largest number of events have low flare rates of $p_f \leq 0.2$ (Figure 11). This is what one would expect when there is an almost low background as a consequence of the open magnetic field. Outside the coronal hole, the average flare rate is $p_f = 0.5$ (Figure 12). It seems that the higher the $p_f$ is, the smoother the background will be. As shown in Figure 13, this would explain why the higher $p_f$ are found in the cell centers (the bright regions of the mentioned figure). The greater the variation of the background is, the lower the $p_f$ value will be. So, this explains why low $p_f$ are seen at the junctions (the dark regions in Figure 13).

The cadence of SDO/AIA (90 s for 2010 August 22) is less than that of STEREO/EUVI (150 s for 2007 June 13). As shown in Figures 8 and 12 (we compare these figures because of their similar average dimensions on pixel regions) the higher the cadence is, the lower the average of the damping time rate (which actually is less than 150/90) will be. For further examination, we produced AIA light curves with cadences of 90 and 180 s (for both regions partitioning $3 \times 3$ and $5 \times 5$ pixels) from the test region in Figure 1. Again the light curves were fed to the network and the frequency distribution of $\alpha$, $\tau_d$, and $p_f$ were shown in Figures 14 and 15. As shown in these figures, there is no change in the average $\alpha$ and $p_f$ with changing cadences, but the average $\tau_d$ decreases while the cadence increases.

Figure 13. Low $p_f = 0.1$ events (red points) fall in the supergranule junctions (dark regions) and the high $p_f = 0.9$ events (yellow points) fall in the supergranule cell centers (light regions). The image was cropped from the full disk image of SDO/AIA 1600 Å on 2010 August 22.

(A color version of this figure is available in the online journal.)

Figure 14. Frequency distribution of $\alpha$, $\tau_d$, and $p_f$ for the light curves of SDO/AIA (Figure 1, test region) with cadences of 90 s (top panel) and 180 s (bottom panel), which were constructed by averaging the intensities of the smaller region ($3 \times 3$ pixels).
7. CONCLUSIONS

The basic aim of the model, as mentioned earlier, is to determine the coronal heat input by numerous randomly distributed small-scale events, especially nanoflares, by finding the power-law index. This will decide whether the small-scale event contribution is of importance or not. The problem of the power-law index indicated by researchers may just have been a bias due to the neglect of overlapping nanoflares.

Here, a simple nanoflare model based on three key parameters (the flare rate, the flare decay time, and the power-law exponent of the flare energy frequency distribution) is used to simulate emission line radiances from the STEREO/EUVI and SDO/AIA in the corona. The simulation code generated more than 22,000 light curves (train set) for each combination of \( \alpha, \tau_d, \) and \( p_f \). Each of the marked regions on the full solar disk images, more than 15,000 light curves were generated for average intensities. This large number of perfect light curves, which enables us in statistical description, was the focus of the present paper. Light curve pattern recognition by a PNN was employed to determine values of the key parameters. We found that more than 85% of the observed light curves have a power-law index greater than 2. Since the network’s sensitivity in the training set in which the network must see all the possible patterns during the training session, we may have some errors in recognizing the correct patterns. Empirically, the network is sensitive to steps \( \Delta \tau_d \approx 1, \Delta p_f \approx 0.1, \) and \( \Delta \alpha \approx 0.1 \) for the three key parameters. This means that for shorter steps, the light curves are too similar and the network is not able to classify them.

The results can be summarized as follows.

1. A physical picture of how the model’s parameters affect the simulated light curves is discussed. Decreases in both the average and variance of the light curves are the function of an increasing power-law index (greater \( \alpha \) value corresponds to greater number of small events). The higher moment (skewness and kurtosis) values of the time series are accompanied by increasing \( \alpha, \tau_d, \) and \( p_f \) values (because of the lognormal shape of the distributions). Both the skewness and kurtosis values are positive numbers. The distributions of both simulated and observed light curves are asymmetric (Terzo et al. 2011).

2. The average \( \alpha \) and \( p_f \) did not change with changes in data cadences, but the average \( \tau_d \) is a sensitive function of the decrease in cadence.

3. With regard to the average dimensionless range of \( \tau_d = 40–50 \) s and by multiplying it by a cadence of 2.5 minutes (for STEREO/EUVI, 2007 June 13) and 1.5 min (for SDO/AIA, 2010 August 22), we obtain values of 100–125 minutes and 100–75 minutes, respectively. Assuming that plasma cooling, through the narrowband filter is dominated by radiative cooling, we find that the ranges are consistent with previous results.

4. The effect of the background emission on the flare rate, \( p_f \), is studied. In the coronal hole regions with less background, the majority of events has low flare rates.

The next logical step is to determine the actual flare energies and the total energy input to the corona, which is still a problem to be solved in the future.

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REFERENCES

Aschwanden, M. J. 2004, Physics of the Solar Corona (Springer: New York), 163
Aschwanden, M. J., Alexander, D., Hurlburt, N., et al. 2000, ApJ, 531, 1129
Aschwanden, M. J., & Charbonneau, P. 2002, ApJ, 566, 59
Aschwanden, M. J., & Parnell, C. E. 2002, ApJ, 572, 1048
Bazarghan, M., Safari, H., Innes, D. E., Karami, E., & Solanki, S. K. 2008, A&A, 492, L13
Benz, A. O., & Krucker, S. 1998, Sol. Phys, 182, 349
Cargill, P. J. 1993, Sol. Phys., 147, 263
Cargill, P. J., & Klimchuk, J. A. 1997, ApJ, 478, 799
Hudson, H. S. 1991, Sol. Phys., 133, 357
Klimchuk, J. A. 2006, Solar Phys., 234, 41
Klimchuk, J. A., van Driel-Gesztelyi, L., Schrijver, C. J., et al. 2009, in IAU Trans. 4, Reports on Astronomy, ed. K. van der Hucht (Cambridge: Cambridge Univ. Press), 79
Levine, R. H. 1974, ApJ, 190, 457
Lu, E. T., & Hamilton, R. J. 1991, ApJ, 380, L89
Parker, E. N. 1988, ApJ, 330, 474
Parnell, C. E., & Jupp, P. E. 2000, ApJ, 529, 554
Pauluhn, A., & Solanki, S. K. 2007, A&A, 462, 311
Rosner, R., Tucker, W. H., & Vaiana, G. S. 1978, ApJ, 220, 643
Safari, H., Innes, D. E., Solanki, S. K., & Pauluhn, A. 2007, in Modern Solar Facilities—Advanced Solar Science, 2006, Universitatsverlag Gottingen, ed. F. Kneer, K. G. Puschmann, & A. D. Wittmann (Gottingen: Universitatsverlag Gottingen), 359
Sakamoto, Y., Tsuneta, S., & Vekstein, G. 2009, ApJ, 703, 2118
Specht, D. F. 1988, in Proc. IEEE Int. Conf. Neural Networks, Vol. 1 (New York: IEEE), 525
Specht, D. F. 1990, Neural Netw., 3, 109
Terzo, S., Reale, F., Miceli, M., et al. 2011, ApJ, 736, 111
Vekstein, G., & Katsukawa, Y. 2000, ApJ, 541, 1096
Wasserman, P. D. 1993, Advanced Methods in Neural Computing (New York: Van Nostrand Reinhold), 35
Wülser, J. P., Lemen, J. R., Tarbell, T. D., et al. 2004, Proc. SPIE, 5171, 111