A statistical study on photospheric active-region magnetic nonpotentiality and associated flares during solar cycles 22 – 23

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Abstract. Using photospheric data obtained by vector magnetograph in Huairou Solar Observing Station of China, we have statistically studied the strength evolution of several magnetic nonpotentiality measures, along with a quantified parameter characterizing the active-region magnetic complexity – effective distance, and their relationship with associated flares during the latest 22nd and 23rd solar cycles. And the flare-prediction performance of these magnetic nonpotentiality and complexity parameters is verified by a machine learning technique.

Keywords. Sun: flares, Sun: magnetic fields, Sun: photosphere

1. Introduction

The accumulation of magnetic nonpotentiality in active regions may provide enormous energy for severe solar eruptions such as flares and coronal mass ejections, which are prone to affect the solar-terrestrial environment. At Huairou Solar Observing Station, the Solar Magnetic Field Telescope (SMFT) (Ai & Hu 1986) has been steadily working for more than 20 years. Based on these precious vector magnetograms of active regions, we statistically studied the strength evolution of several magnetic nonpotentiality measures, along with a magnetic complexity parameter – effective distance (Chumak et al. 2004), and also their relationships with associated flares during the latest 22nd and 23rd solar cycles. Within 30° from the solar disk center, only one magnetogram of an active region is picked up each day from all the vector magnetograms. 2173 magnetograms containing 1106 active regions from June 1988 to March 2008 are selected as samples for the calculations. These samples are divided into two parts, the flare-productive part and the flare-quiet one, according to whether the active region produced flares with \( FI \geq 10.0 \) (M1.0 equivalent; FI: flare index, Antalova 1996, Abramenko 2005) within 24 h. Then the yearly mean values of each nonpotentiality parameter are calculated separately for each part. Other values of the FI threshold and following time are adopted as well. Based on these data and flare records, the flaring potential of each active region at its specific observing time is also statistically calculated. Furthermore, an effective machine learning method is used to verify the flare-prediction performance of these magnetic nonpotentiality and complexity parameters.

2. Statistical results

The calculated magnetic parameters of each vector magnetogram are, the mean planar magnetic shear angle \( \Delta \phi \), mean shear angle of the vector magnetic field \( \Delta \psi \), mean absolute vertical current density \( |J_z| \), mean absolute current helicity density \( |h_c| \), absolute twist parameter \( |\alpha_{av}| \), mean free magnetic energy density \( \rho_{free} \), effective distance of the...
longitudinal magnetic field $d_E$, and longitudinal-field weighted effective distance $d_{Em}$. They are all macroscopic and averaged quantities, which represent the nonpotentiality or complexity of a whole active region.

The results show that, $|h_c|$, $\rho_{free}$, and $d_{Em}$ present high correlations with the variation of the solar cycle. The Pearson linear correlation coefficients of the above three with the yearly mean sunspot numbers are larger than 0.59. Meanwhile, the magnitude of $\Delta \phi$ and $\Delta \psi$ around sunspot penumbras and polarity inversion lines, $|J_z|$, $|\alpha_{av}|$, and $d_E$ reveal weak trends of evolution with the solar cycle. However, it is more likely that these five parameters show higher values in the solar maximum than in the solar minimum. The small peak of flare-productive samples in 2005 corresponds to a little more flares in that year. The directly related parameters $\Delta \phi$ and $\Delta \psi$, $d_E$ and $d_{Em}$, and $|h_c|$ and $|J_z|$ are highly correlated with each other as expected. The parameters $|h_c|$ and $\rho_{free}$ also show very high correlation. All of the studied measures show positive correlations with the flare productivity of active regions. Due to the loss of information of magnetic field strength in the parameter of effective distance $d_E$, the modified effective distance $d_{Em}$ (including the strength of the magnetic field) turns out to be much better in indicating the magnetic activities of active regions. More detailed description of the statistical work and results can be found in Yang et al. (2012). In addition, the scatter-point plots in that paper only reveal the divisions according to a particular flare-index threshold, and the relationships between soft X-ray flare index and each magnetic measure are complicated and irregular.

3. Prediction experiments

Many works have showed that there is a close relationship between magnetic nonpotentiality and solar flares. Based on the statistical work done above, we are trying a general classifier, which applies one of the learning machine method, to predict whether there would be a flare in an active region within a certain time window. The predictors are the magnetic nonpotentiality parameters, which are used as the inputs of the classification model. The training and testing data are from the 2173 vector magnetograms mentioned in Section 1. We adopt several verification skill scores to synthetically assess the performance of the predictions. The preliminary results show that the combination of different nonpotentiality parameters will be effective in assessing the flaring probability of active regions. It is possible to estimate the rough time and magnitude of the flare. The corresponding results of this work is in preparation. Based on our experiments, a realtime flare prediction system could be built with the practical observation of vector magnetic fields in the solar photosphere.

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