## Prediction of solar magnetic cycles by a data assimilation method

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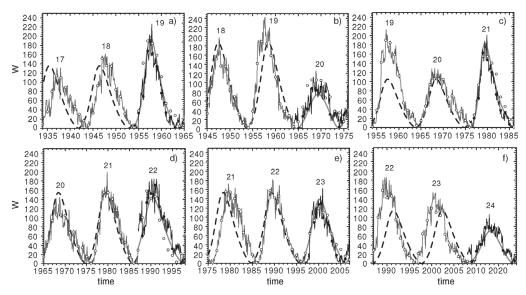
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Abstract. We consider solar magnetic activity in the context of sunspot number variations, as a result of a non-linear oscillatory dynamo process. The apparent chaotic behavior of the 11-year sunspot cycles and undefined errors of observations create uncertainties for predicting the strength and duration of the cycles. Uncertainties in dynamo model parameters create additional difficulties for the forecasting. Modern data assimilation methods allow us to assimilate the observational data into the models for possible efficient and accurate estimations of the physical properties, which cannot be observed directly, such as the internal magnetic fields and helicity. We apply the Ensemble Kalman Filter method to a low-order non-linear dynamo model, which takes into account variations of the turbulent magnetic helicity and reproduces basic characteristics of the solar cycles. We investigate the predictive capabilities of this approach, and present test results for prediction of the previous cycles and a forecast of the next solar cycle 24.

**Keywords.** Sun: activity – magnetic fields – sunspots

One of the manifestations of solar magnetic activity is the 11-year sunspot cycle, which is characterized by the fast growth and slowly decay of the sunspot number parameter. For an explanation of the magnetic field generation Parker (1955) proposed a simple  $\alpha\Omega$ -dynamo model, which describes the phenomenon as an action of two factors: the differential rotation and cyclonic convective vortices. For modeling the solar cycle we consider non-linear solutions of the Kleeorin-Ruzmaikin model (Kleeorin & Ruzmaikin, 1982), which in addition to the  $\alpha\Omega$ -dynamo process describes the evolution of the magnetic helicity based on the balance between the large-scale and turbulent magnetic helicities. To connect the dynamo model solutions with the sunspot number data we use two suggestions of Bracewell (1988): the periodical reversals of the magnetic field are represented in the sunspot number series by assigning alternating positive and negative signs to the sunspot cycles, and the sunspot number is modeled in the form of a three-halfs law:  $W \sim B^{3/2}$ , where W is the sunspot number, and B is the strength of the Sun's toroidal magnetic field. Our analysis of the Parker-Kleeorin-Ruzmaikin dynamo model shows the existence of nonlinear periodic and chaotic solutions for conditions of the solar convective zone (Kitiashvili & Kosovichev, 2009). For this model we obtained solutions with the profiles of W, which qualitatively reproduce the typical profile of the sunspot number variations of the solar cycles.

For predicting the solar cycle properties we make an initial attempt to use the Ensemble Kalman Filter (EnKF), a data assimilation method, which takes into account uncertainties of the dynamo model and the observed sunspot number series (Evensen, 2007). This method has been tested by calculating predictions of the past cycles using only the observational data (annual sunspot numbers) until the start of these cycles. Figures 1 a-e show examples of the EnKF method implementation for the forecasting of



**Figure 1.** Predictions for solar cycles 19–24. Grey curves show variations of the sunspot number according to the known observation data (empty circles) and black curves represent the EnKF estimates for the following (predicted) cycles.

solar cycles 19–23. In this approach the exact model solution is corrected according to the observational data when these become available. This allows us to redefine the initial conditions of the model for the magnetic field components and helicity, and construct a model solution for the next time interval. To estimate the uncertainties we added noise to the model (in the form of a random forcing function) and to the simulated data, and calculated a statistical mean and error an estimate, following the EnKF procedure. We note that the errors of the predictions depend also on the number of measurements in the simulated ensemble, and also on the determining the moment of the end of the last observed cycle. The similar analysis scheme is used for predicting of the upcoming solar cycle 24 (Fig. 1f). According to our analysis, the solar cycle 24 which starts in 2008–2009 yrs. will be weaker than the current cycle by approximately 30% (Kitiashvili & Kosovichev, 2008). The estimated formal error of our prediction is  $\sim 10\%$ .

The application of the EnKF method for modeling and predicting solar cycles shows the power of this approach and encourages further development.

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