Chapter 7

Conclusion

In this chapter, I would like to summarize the results of the thesis and discuss the new findings in brief. The thesis mainly focuses on explaining the observed features of the long-term evolution of the solar cycles and explores the novel methodologies for long-term prediction of solar cycles as well as the forecast of short-term space weather impacts. In this work, I have extensively utilized 2D, and 3D dynamo simulations, and SFT simulations for a detailed understanding of the intricate processes involved in the evolution of Sun's magnetic field. As the near-Earth space weather phenomena driven by solar activity significantly impact many aspects of our technology-driven society, the ultimate frontier of space weather studies is the reliable forecast of the near-Earth impact of the energetic phenomena on the Sun. To explore this aspect, we used machine learning algorithms aided by forward modelling techniques for better predictability of geomagnetic storms that occurred by the CMEs.

The observations of Waldmeier (1955) regarding the similarity in different solar cycles during their decline phases were unexplored and unexplained for a long time until Cameron and Schüssler (2016) brought it back to the forefront of the research with their detailed analysis of century-scale solar observations. Using 2D axisymmetric dynamo simulations, Chapter 2 delves into the search for the nonlinear process that can make all cycles behave similarly. It is found that the nonlinear loss of toroidal flux from the solar interior due to the emergence of toroidal flux tubes is an essential mechanism to explain the observations. Due to this process, the strong cycles lose much higher amounts of flux than the weaker cycles during their beginning phases as the strong cycles produce much more sunspots than the weaker ones in this phase. This phenomenon makes all the cycles have similar amounts of flux during their decline phases hence all cycles decline with similar statistical properties.

From the direct observations and the reconstructed long-term data of solar cycles, it has been known that solar activity shows significant variability within a wide range with occasional periods of very low activity, known as grand minima, and on the other hand, there are periods of very high activity which are known as the grand maxima. There has been a significant amount of research done to explain these behaviours of solar activity. In Chapter 3, we discuss a few nonlinear processes that work as negative feedback to the solar dynamo, i.e. whenever the magnetic field of the Sun grows stronger, these nonlinear mechanisms become stronger as well and their combined effect stabilizes the solar dynamo stopping the sequential growth of the consecutive solar cycles. On the other hand, We also demonstrate the effects of crucial stochastic processes in the solar dynamo primarily due to the fluctuations in the various properties of the BMRs, that drive the long-term variability of the solar cycles, occasionally leading it to the grand minima episodes. The inclusion of these processes in the 3D dynamo simulations has satisfactorily reproduced the long-term trend of solar cycle evolution similar to the observations.

Due to the highly variable nature of solar activity, it is very hard to predict the strength of an upcoming cycle well in advance. However, the prediction of solar cycles is crucial for the understanding of the overall space weather conditions in the upcoming years. Traditionally, the polar field strength during the minima of a cycle has been used for the prediction of the following cycle with a prediction window of about 3–5 years. In Chapter

4 we explore the robustness of the observed correlation between the polar field rise rate and the peak strength of the following cycle under the impact of stochastic and anomalous properties of the BMRs. We find that the observed correlation between these two quantities is an intrinsic feature of the solar cycles and it can be utilized to predict the strength of the upcoming cycle much earlier than the cycle minima with a possible prediction window of 6–8 years.

As the rising rate of the polar field is calculated from the time of polar field reversal, it becomes an important landmark in the evolution of solar cycles. However, in observations, it has been found that the polar field reversal timing varies significantly from one cycle to the other. The reason behind the phenomena of different cycles taking different amounts of time to achieve polarity reversal has been explored in Chapter 5. It has been found that the varied presence of the anomalous BMRs can be one of the primary reasons behind the observed variations, also the so-called anti-Hale BMRs are found to be a higher source of disturbance for the polar field evolution than the other types (like the anti-Joy BMRs) of anomalous properties of the BMRs.

The most severe impact of the space weather disturbances driven by the solar magnetic activities manifests in the form of the geomagnetic storms, that occur due to the interactions of CMEs with the Earth's magnetosphere. To mitigate this impact, it is absolutely necessary to build reliable systems that can predict when a CME can reach Earth and how much would be the impact of it. The longest possible window of this forecast can be achieved by utilizing the properties of the CME when it evolves near the Sun as an input to assess its near-Earth implications. Chapter 6 contains a study where one of the most reliable forward modelling techniques, namely the GCS model has been utilized to estimate various properties of the CME as it leaves the solar atmosphere. These properties of the CME along with the observed timing and impact of the associated geomagnetic storm have been used to train an Artificial Neural Network. This network has shown reliable performance when tested on a new set of events and predicted the transit times of the CMEs from the Sun to Earth with a minimal mean absolute error of 4.22 hrs and standard deviation of 2.80 hrs, on the other hand the mean absolute error for the prediction of the minimum value of Dst index during the associated storm is 12.39 nT with a standard deviation of 10.28 nT. These results establish that machine learning algorithms can be reliably used for making reasonable forecasts of space weather events and the performance of these algorithms can be improved in the future with larger sets of training data acquired from further observations.