Progress in Solar Cycle Predictions: Sunspot Cycles 24–25 in Perspective

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Abstract The dynamic activity of the Sun—sustained by a magnetohydrodynamic dynamo mechanism working in its interior—modulates the electromagnetic, particulate, and radiative environment in space. While solar activity variations on short timescale create space weather, slow long-term modulation forms the basis of space climate. Space weather impacts diverse space-reliant technologies while space climate influences planetary atmospheres and climate. Having prior knowledge of the Sun’s activity is important in these contexts. However, forecasting solar-stellar magnetic activity has remained an outstanding challenge. In this review, predictions for Sunspot Cycle 24 and the upcoming Solar Cycle 25 are summarized, and critically assessed. The analysis demonstrates that while predictions based on diverse techniques disagree across Solar Cycles 24–25, physics-based predictions for Solar Cycle 25 have converged and indicates a weak to moderate–weak sunspot cycle. I argue that this convergence in physics-based predictions is indicative of progress in the fundamental understanding of solar cycle predictability. Based on this understanding, resolutions to several outstanding questions related to solar cycle predictions are discussed; these questions include: is it possible to predict the solar cycle, what is the best proxy for predictions, how early can we predict the solar cycle and how many cycles into the future can we predict relying on our current understanding? Based on our analysis, we also suggest a rigorous pathway towards generating and disseminating a “consensus forecast” by any solar cycle prediction panels tasked with such a challenge.

Dedicated to the memory of Bernard Durney.

This article belongs to the Topical Collection:
Towards Future Research on Space Weather Drivers
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1. The Case for Solar Cycle Predictions

The space environment in the solar system is governed by the variable activity of the Sun. This variability is manifested in changing flux of solar radiation, solar energetic particles, solar magnetic fields, and a variable solar wind output. Occasionally, energetic events such as flares and coronal mass ejections (CMEs) introduce extreme perturbations in our space environment. These phenomena are collectively referred to as space weather. Severe space weather can impact the health of satellites and astronauts in outer space, disrupt satellite-based communications and navigational networks, high frequency radio communications, electric power grids, oil pipelines, and air-traffic on polar routes. Understanding, assessing and predicting space weather is therefore critical to protection of modern day technologies and is considered a high priority research area (National Research Council, 1997, 2013; National Science and Technology Council, 2019; Krausmann et al., 2016; UNOOSA Space Weather, 2017; Schrijver et al., 2015).

Slower, longer-term modulation in the solar activity output over timescales ranging from decades to centuries to millennia (Solanki et al., 2004; Usoskin, 2017) define what is known as space climate (Versteegh, 2005). Space climate plays a role in the forcing of planetary atmospheres, e.g., in the heating of the upper atmosphere and its expansion which is relevant for satellite drag and mission life-time estimates. While magnetically modulated variations in the solar irradiance provide a link to planetary climate systems (Solanki and Krivova, 2003), solar open flux variations determine the flux of galactic cosmic rays at Earth (Usoskin et al., 2002). Secular variations in the Sun, solar wind and interplanetary magnetic flux also impact planetary magnetospheres with consequences for geomagnetic activity (Mursula, Zieger, and Vilppola, 2003) and atmospheric evolution (Das et al., 2019). Indeed, the intimate relationship between solar-stellar activity and the planets that they host can extend over their coupled lifetimes and is based on causal connections between physical processes in stellar interiors and planetary atmospheres (Nandy and Martens, 2007).

Stripped bare to its roots, at the fundamental level space weather and space climate are products of the solar magnetic cycle and its diverse manifestations—which are consequences of the emergence, evolution and dynamics of solar magnetic fields or sunspots and their impact on the heliospheric environment. Thus, the quest to assess and forecast our space environment is intimately related to, and contingent upon understanding the physics of the solar magnetic cycle. Development of solar cycle predictive capabilities based on this understanding is an outstanding challenge in heliophysics.

Solar magnetic fields are generated by a magnetohydrodynamic (MHD) dynamo mechanism that is sustained by complex interactions between plasma flows and magnetic fields in the Sun’s convection zone (Parker, 1955a; Babcock, 1961; Leighton, 1969; Charbonneau, 2020). The toroidal component of the dynamo generated magnetic field buoyantly emerges through the solar surface creating sunspots—strongly magnetized, and relatively darker regions on the solar surface. Sunspots have been monitored for over four centuries starting with the pioneering observations of Galileo Galilei. Their magnetic nature was discovered in the early 20th century (Hale, 1908). Development of the magnetograph instrument (Babcock and Babcock, 1955) allowed observations of the large-scale (relatively weaker) magnetic field that exists outside of sunspots and which plays a crucial role in the build-up of

Keywords Solar activity · Sunspots · Solar cycle prediction · Magnetohydrodynamics · Solar dynamo
the polar flux leading to the reversal of the global dipolar field (i.e. the poloidal component of the dynamo generated magnetic field).

These long-term observations illuminate various facets of the sunspot cycle on the one hand (Hathaway, 2015) and on the other hand, provide important constraints on the solar dynamo mechanism (Nandy and Choudhuri, 2002) and motivate various approaches for solar cycle predictions (Petrovay, 2020).

2. Sunspot Cycle Observations: The Prediction Challenge

Long-term observations indicate that the number of sunspots on the solar surface (which is a proxy for the toroidal component of the solar magnetic field) increases and decreases in a cyclic fashion with an average periodicity of 11 years. Barring episodes of grand minima in activity, e.g., the Maunder minimum, this trend has been maintained over the last four centuries. In Figure 1 we present an overview of solar cycle observations over the last 100 years and establish century-scale solar cycle climatological trends of relevance to cycle predictions. Figure 1a presents the (revised) sunspot number time series covering Solar Cycles 15–24. It is evident that while the solar cycle period varies only slightly from cycle to cycle, there is significant variability in its amplitude—quantified by the (annual averaged) peak sunspot number. From these observations we establish a century-scale mean sunspot cycle amplitude $184.6 \pm 44.3$ ($\sigma$ is the standard deviation in the figure). The climatological mean is indicated by the red-dashed line, while the range (mean $\pm 1\sigma$) is indicated by the shaded region in Figure 1a. We define cycles whose peak lies within the shaded region (mean $\pm 1\sigma$) as moderate solar cycles; cycles which lie within this region but are higher than the mean may be further sub-classified into moderate–strong cycles and cycles which lie below the mean may be sub-classified in to moderate–weak cycles. Extreme solar cycles which lie over this region (greater than mean $+1\sigma$) are classified as strong cycles and cycles which lie below this range (mean $-1\sigma$) are classified as weak cycles. We note that only one cycle (19) has been extremely strong, while two solar cycles (16 and 24) have been extremely weak. In fact the recently concluded Solar Cycle 24 has been the weakest cycle of the past century. There is no discernible pattern in amplitude variability from one cycle to another in the sunspot time series which makes their prediction a challenging task.

The variation of the Sun’s polar flux, which is a proxy for the poloidal component of the solar magnetic cycle is depicted in Figure 1b. This time series is based on Mount Wilson Observatory calibrated polar faculae data (Muñoz-Jaramillo et al., 2012). The (radial) polar fluxes in the solar north and south poles are found to be opposite to each other indicative of a global dipole field configuration near solar minima. The polar fields also undergo cyclic reversals. They are the weakest and reverse their sign (polarity) during sunspot maxima and they are the strongest during sunspot cycle minima; the polar field lags the sunspot cycle (i.e., the toroidal field component) with a phase difference of $90^\circ$. In fact, although not evident here, the relative orientation of bipolar sunspot pairs reverse orientation from one cycle to another, indicating that the toroidal component of the solar magnetic field also reverses from one sunspot cycle to another.

A pattern emerges when one compares the amplitude of the polar flux (Figure 1b) at sunspot cycle minima with the strength of the following sunspot cycle (Figure 1a). A stronger polar field at solar minimum, in general, is indicative of a stronger (following) sunspot cycle maximum. There is causality in this observation, as the solar polar field acts as the seed which is further amplified by the Sun’s differential rotation to produce the next
Figure 1 Solar cycle observations. The solid green curve in Figure 1a depicts the sunspot time series from 1914.5 to 2019.5. This time series is generated utilizing the revised version of the annually averaged new sunspot number data (Clette et al., 2015) acquired from the World Data Center, Sunspot Index and Long-term Solar Observations (SILSO). The red-dashed line denotes the mean (184.6) of all cycle amplitudes during this period and the shaded portion indicates $1\sigma$ (44.3) variation around the mean. In Figure 1b, we show the evolution of the polar hemispheric flux derived from Mount Wilson Observatory calibrated polar faculae data (Muñoz-Jaramillo et al., 2012) covering 1914 to 2014. This data is acquired from the solar dynamo database maintained by Andrés Muñoz-Jaramillo. We extend this plot with the calibrated Wilcox Solar Observatory polar field data till 2019.5. The blue (red) curve represents the polar flux in northern (southern) hemisphere. In Figure 1c we plot the sunspot butterfly diagram. The data for the butterfly diagram is acquired from the Royal Greenwich Observatory/USAF-NOAA active region database compiled by David H. Hathaway for the period 1914 to 2016. The subsequent data until 2019 is acquired from the Helioseismic and Magnetic Imager (HMI) instrument (Scherrer et al., 2012) on board the Solar Dynamics Observatory (SDO: Pesnell, Thompson, and Chamberlin, 2012). Solar cycle numbers are indicated in the top and bottom panels.

sunspot cycle. This causal connection is the basis of one of the more successful empirical prediction techniques—the precursor method.

Figure 1c depicts the solar butterfly diagram, which indicates that there is also a spatio-temporal pattern in the sunspot cycle. Cycles begin with sunspots appearing at mid-latitudes, with more and more spots appearing at lower and lower latitudes as the cycle progresses. This pattern is followed in both the hemispheres with the cycle eventually ending with sunspots appearing only close to the equator. This pattern repeats from one cycle to another
Figure 2  Revision of the sunspot number time series. Sunspot number time series has been revised to get rid of the temporal inhomogeneities (the new version V2.0 has been updated at World Data Center SILSO, Royal Observatory of Belgium in 2015). A detailed synopsis of this revision can be found in a study by Clette and Lefèvre (2016). As more than 10 predictions for Solar Cycle 25 have been published based on the old SSN, it is essential to scale them appropriately for a comparative analysis. Here we compare the old version of the SSN time series with the new version. The new (old) sunspot number time series has been plotted in solid black (red) curve which is shown in panel a. In panel b the solid black curve shows the time series of the ratio between new sunspot number and the old sunspot number. It is important to note that the mean ($\pm 1\sigma$) of the ratio after 1950 is $1.43 \pm 0.1$. We have used this scaling factor to scale up the predictions published on or before 2015.

and this distribution of sunspots is explained on the basis of a deep seated counter-flow in the meridional circulation within the solar convection zone (Nandy and Choudhuri, 2002).

Ideally, one would expect that advances in understanding the solar dynamo mechanism and advances in methodologies for accurate solar cycle predictions would be commensurate with each other. This expectation would imply that attempts at solar cycle predictions must also imbibe many of the constraints available from solar cycle observations, and be able to explain most, if not all, features of the spatio-temporal variability in the sunspot cycle. This is the rather restrictive view that is taken in categorizing physics- or model-based predictions in this review with the additional consideration that this class of predictions must also be based on MHD models of the solar magnetic field evolution. Nevertheless, several other techniques—ranging from some which have no connection with the underlying physics whatsoever to some which draw inspiration from the underlying physics—have been utilized for forecasting the solar cycle. In the next section we revisit such predictions for Solar Cycle 24 and in the subsequent section we present predictions made until now for Solar Cycle 25. These predictions are further analyzed and compared in subsequent sections to ascertain any apparent progress over the last decade in solar cycle prediction efforts.

Note that the numbers for the predicted cycle amplitude in figures presented in this review have been scaled to conform to the new, revised sunspot time series (Clette et al., 2015) for ease of comparative analysis and thus numbers are different from those in earlier reviews (Pesnell, 2008, 2012). Figure 2 depicts Versions 1 and 2 (V2.0) of the sunspot time series.
along with the time variation of the ratio of these series. Based on this figure, we determine that a multiplicative factor of 1.43 is a convenient method for scaling predictions based on the old time series to correspond to the new, revised sunspot time series. This may introduce minor variations relative to the comparative study in Pesnell (2008). In the text description of diverse Solar Cycle 25 predictions (Section 4), however, we have maintained the numbers as generated by diverse groups (i.e., we have not scaled them) such that the reader can understand the impact of this scaling.

## 3. Predictions of Solar Cycle 24

Solar Cycle 24 commenced following a series of sequentially weaker solar cycles and an unusually extended minimum of Sunspot Cycle 23 (Nandy, Muñoz-Jaramillo, and Martens, 2011). Multiple predictions were made for Solar Cycle 24. Following (Pesnell, 2008, 2012) in Figure 3, we summarize the predictions of Solar Cycle 24. In this figure, predictions have been categorized based on the underlying methodology utilized for making the forecast for the peak cycle amplitude. The observed peak amplitude of Solar Cycle 24 is depicted in Figure 3 with a gray-dashed line.

An analysis of Solar Cycle 24 predictions in Figure 3 reveals that a majority of the forecasts predicted a much higher cycle than what was observed. The mean (± 1σ) of all the Solar Cycle 24 predictions is 163.1 ± 42.2 in units of sunspot number (SSN). The observed peak (113.3 SSN) was outside the range of these predictions! Clearly, there was no convergence in predictions utilizing the diverse techniques.

Evidently, there is no physical meaning in arriving at a mean or an average forecast from such diverging predictions employing unrelated and disparate techniques; any solar
cycle prediction panel should keep this in mind. Nonetheless, as we shall see, the mean and standard deviation of different cycle predictions across different cycles may provide a purely pragmatic method to assess relative consensus among techniques.

The two physical (dynamo) model based predictions by Dikpati, de Toma, and Gilman (2006) and Choudhuri, Chatterjee, and Jiang (2007) predicted very strong and very weak cycles, respectively. Although the latter prediction for a weak cycle turned out to match observations, it was not immediately obvious why, and the non-convergence in physics-based forecasts led to massive heartburn and controversies that shook the field. To make matters worse the NOAA-NASA Solar Cycle Prediction Panel made an early declaration of a strong cycle and subsequently had to revise the forecast to a weak cycle after the cycle had already started. At one point, the NOAA-NASA panel issued a statement indicating Cycle 24 could be very strong, or very weak (Biesecker, 2007)! Perhaps the early panel statement was motivated from the perspective of achieving a consensus based on the many (early) strong-cycle forecasts and it may have been particularly influenced by the Dikpati, de Toma, and Gilman (2006) forecast which was based on a physical model.

It is natural that anyone looking at the “confusogram” of forecasts for Solar Cycle 24 – their non-convergence and disagreement with the eventually observed Solar Cycle 24 peak – would conclude that the understanding of solar cycle predictability was at a very immature stage at this juncture. In hindsight of Solar Cycle 24 and now armed with knowledge of recent predictions for Sunspot Cycle 25 at the intervening cycle minimum, one is tempted to pose the question, are we any better off a decade down the line and one solar minimum later? To assess the current scenario, we present predictions for Solar Cycle 25 in the next section and analyze them.

4. Predictions of Solar Cycle 25

In Figure 4 we present predictions of the peak amplitude of Sunspot Cycle 25 from various groups using a diversity of techniques. We also summarize the predictions in Table 1. For predictions made before the year 2016, we have scaled the predicted amplitude to conform to the revised sunspot time series but have left the numbers unchanged for predictions published in the year 2016 or thereafter; i.e., we have assumed that predictions published in the year 2016 and thereafter have been calibrated with the new sunspot time series released in 2015 (Clette et al., 2015). First, we categorize Solar Cycle 25 predictions based on the utilized methodology and provide a brief narrative summary of each of the predictions.

4.1. Physical Model Based Forecasts (MB)

i) Bhowmik and Nandy (2018) utilized an observational data driven, century scale calibrated Surface Flux Transport (SFT) model whose output was coupled to a solar internal dynamo model to predict Solar Cycle 25. They predicted that Solar Cycle 25 would be similar or slightly stronger than Solar Cycle 24 with a peak SSN of 118, with an ensemble forecast (uncertainty) range of 109 – 155. This would place Solar Cycle 25 in the weak to moderate–weak regime. Bhowmik and Nandy (2018) also predicted that the peak of Solar Cycle 25 would occur in 2024 (± 1 year).

ii) Jiang et al. (2018) predicted Solar Cycle 25 utilizing a solar Surface Flux Transport (SFT) model. They used the correlation between the axial dipole moment at cycle minimum and the subsequent cycle strength and the other empirical properties of solar cycles to predict the possible behaviors of the succeeding cycle. Their predicted a peak SSN of 125 ± 32.
Figure 4 Predictions of Solar Cycle 25 by different groups based on diverse methodologies (indicated in the plot and represented through distinct color bars). The height of the bars indicate the predicted peak strength (scaled to conform to the new, revised sunspot time series). The mean ($\pm 1\sigma$) of all Solar Cycle 25 predictions is $136.2 \pm 41.6$ (SSN). The dashed line denotes the observed peak of Solar Cycle 24 (113.3 SSN in the revised scale) for comparison. Details of the utilized methodologies can be found in the references cited below the corresponding predictions.

iii) Upton and Hathaway (2018) used their Advective Flux Transport (AFT) model and the empirical (precursor) relationship between the polar field and the subsequent cycle amplitude to predict the SSN. According to them Solar Cycle 25 would be slightly weaker than Solar Cycle 24. They predicted a maximum sunspot number (SSN) of 110.

iv) Labonville, Charbonneau, and Lemerle (2019) used a data-driven hybrid 2 $\times$ 2D flux transport dynamo (FTD) model to forecast properties of the upcoming sunspot Cycle 25. They predicted that the maximum SSN for Solar Cycle 25 would be between $89 \pm 29$.

The peak was predicted to occur between 2025.3 $\pm$ 0.89.

v) Cameron, Jiang, and Schüssler (2016) utilized an SFT model to evaluate the polar field at the minimum of Solar Cycle 24 and based on this made an assessment of Solar Cycle 25. They concluded that the amplitude of Solar Cycle 25 will be slightly larger than that of Solar Cycle 24. However, they did not predict an exact numerical value for the peak strength and therefore this prediction is not included in Figure 4.

vi) Iijima et al. (2017) used an SFT model and studied how the axial dipole moment varies near the solar minimum. Based on the plateau of the predicted axial dipole moment they predicted that Solar Cycle 25 will be weaker than the previous cycle. Their prediction is also excluded from Figure 4 because they did not estimate a numeric value for the amplitude of Solar Cycle 25.
4.2. Precursor Technique Based Forecasts (P)

i) Pesnell and Schatten (2018) utilized the solar dynamo (SODA) index that combines values of the solar polar magnetic field and the solar spectral irradiance at 10.7 cm to create a precursor of future solar activity. They predicted a maximum SSN of $135 \pm 25$ occurring in 2025.2 $\pm 1.5$.

ii) Hawkes and Berger (2018) calculated the helicity flux through both hemispheres using a model that takes into account of the Omega effect, using the magnetic field data from Wilcox Solar Observatory (WSO) covering a total of 60 years. Using various correlation analysis between helicity flux and the sunspot time series they predicted the amplitude of Solar Cycle 25 to be 117 which is slightly higher than that of Solar Cycle 24.

iii) Petrovay et al. (2018) used the Rush To The Poles phenomenon (RTTP) in coronal green line emission to predict the peak SSN for Solar Cycle 25. Based on the correlation between the rate of the RTTP and the time delay until the maximum of the next solar cycle, and the known internal regularities of the sunspot number series, they predicted that the peak amplitude to be 130 occurring in late 2024.

iv) Gopalswamy et al. (2018) used the polar and low-latitude brightness temperatures as proxies for the polar magnetic field to predict Solar Cycle 25. The polar microwave brightness temperature was found to be correlated with the polar magnetic field strength and the fast solar wind speed. These correlations were used to predict a maximum SSN of 89 in the south and 59 in the northern hemisphere (unsmoothed SSN), 116 in south and 97 in north (smoothed SSN).

v) Helal and Galal (2013) used a solar activity precursor technique of spotless events to predict the maximum SSN of Solar Cycle 25 which would be 118.2. According to this study the upcoming cycle will peak between 2022-2023.

vi) Hazra and Choudhuri (2019) used a composite formula utilizing sunspot data from the Solar Influences Data Analysis Center (SIDC) and polar field data from WSO with two different least squares fit to predict a peak SSN of 138-143 for Solar Cycle 25.

vii) McIntosh et al. (2020) performed a discrete Hilbert transform analysis and identification of cycle “termination” epochs (following Leamon et al., 2020 to predict a historically strong Solar Cycle 25 with SSN of 233.

4.3. Non-linear Model Based Forecasts (N)

i) Sarp et al. (2018) implemented a non-linear prediction algorithm based on delay-time and phase space reconstruction to forecast a maximum SSN of $154 \pm 12$ occurring in 2023.2 $\pm 1.1$.

ii) Sello (2019) used revised non-linear dynamics methods to predict the maximum SSN for Solar Cycle 25 to be $107 \pm 10$ occurring in July 2023 $\pm 1$ year.

iii) Kitiashvili (2020) applied an ensemble Kalman filter method to predict solar cycles using a non-linear system of equations that is intended to mimic a truncated mean-field dynamo model. They used data assimilation to predict a maximum SSN of $50 \pm 15$ occurring around 2024-2025.

4.4. Statistical Forecasts (S)

i) Li, Feng, and Li (2015) found that the ascent duration (AD) of a solar cycle is statistically related to the descent duration (DD) of the cycle. Statistical relations among feature parameters of the solar cycle were used to predict the behaviour of Solar Cycle 25. The maximum SSN is predicted to be 109.1 occurring around October 2023.
ii) Pishkalo (2008) used the correlation between cycle parameters to predict the SSN for Solar Cycle 25. According to this study the peak SSN would occur on 2023.4 ± 0.7 with an amplitude of 112.37 ± 33.4.

iii) Li et al. (2018) utilized relations among the feature parameters of solar cycles under the bimodal distribution for the modern era cycles (Cycles 10–23). These relations are utilized to predict that Solar Cycle 25 would initiate in October 2020 and reach its maximum amplitude of 168.5 ± 16.3 in October 2024.

iv) Singh and Bhargava (2017) performed a statistical test for persistence of solar activity based on the value of the Hurst exponent (H). They predicted that the maximum SSN would occur on June 2024 with a value of 102.8 ± 24.6.

v) Han and Yin (2019) implemented the Vondrak smoothing method to produce a series of smoothed SSN (denoted SSN-VS)—which closely mimics the 13-month running mean SSN. Applying these techniques to the descending phase of Solar Cycle 24 they make predictions for Solar Cycle 25 whose peak is estimated to be 228.8 ± 40.5 occurring in 2023.92 ± 1.64 year.

vi) Hathaway and Wilson (2004) studied various relations between time period, rise time, sunspot maxima and minima, and hemispheric asymmetries. Based on this analysis they predicted that the maximum of Solar Cycle 25 will occur in 2023 with peak amplitude 70 ± 30.

vii) Du and Du (2006), based on their analysis, claimed that the amplitude of a solar activity cycle is correlated with the descending time of the \([n - 3]\) cycle. Based on this correlation they predict a peak SSN of 111.6 ± 17.4.

viii) Hiremath (2008) modeled solar cycles considering a forced and damped harmonic oscillator. They obtained long-term amplitudes, frequencies, phases, and decay factors from 22 cycles (1755–1996). Using these parameters and employing an autoregressive model they predicted a maximum SSN of 110 ± 11 occurring in 2023.

ix) Abdusamatov (2007) analyzed the long-term cyclic variations of solar activity, radius, and solar constant claiming them to be correlated in both phase and amplitude. Based on this they predicted a very low Solar Cycle 25 peak of 50 ± 15.

x) Kakad, Kumar, and Kakad (2020) estimated the Shannon entropy (computed using histogram derived probability distribution function (PDF) and kernel density estimator derived PDF) related to the declining phase of the preceding solar cycle which is used to predict the SSN. Two SSN maxima for two different methods are estimated to be 136.9 ± 24 and 150.7 ± 25. The mean of these two values is 143.8 ± 25

4.5. Spectral Methods Based Forecasts (SP)

i) Kane (2007b) used spectral analysis of the sunspot time series to detect periodicity by the maximum entropy method (MEM). The periodicity obtained is further utilized in a multiple regression analysis (MRA) to estimate the amplitude of Solar Cycle 25 to be between 112-127 with a mean value of 119 occurring around 2022-2023.

ii) Rigozo et al. (2011) decomposed monthly sunspot number data during the 1850-2007 interval (Solar Cycles 9–23) into several levels and searched for periodicity by iterative regression at each level. Their prediction was based on extrapolation of the SSN time series spectral components. They estimated a maximum SSN of 132.1 occurring in April 2023.

iii) Javaraiah (2015) studied the combined Greenwich and Solar Optical Observing Network (SOON) sunspot group data during 1874-2013. They analyzed and studied the relatively long-term variations in the annual sums of the areas of sunspot groups in
0° – 10°, 10° – 20°, and 20° – 30° latitude intervals of the Sun’s northern and southern hemispheres using the fast Fourier transform (FFT), maximum entropy method (MEM), and Morlet wavelet analysis. Long-term variations in the north–south asymmetry of solar activity is used to predict a SSN of 50 ± 10.

4.6. Machine Learning and Neural Network Based Forecasts (ML/NN)

i) Dani and Sulistiani (2019) used machine learning methods of Linear Regression (LR), Random Forest (RF), Radial Basis Function (RBF), and Support Vector Machine (SVM) to predict the peak SSN for Solar Cycle 25. Predicted peak amplitudes were 159.4 ± 22.3, 110.2 ± 12.8, 95.5 ± 21.9, and 93.7 ± 23.2 occurring in September 2023, December 2024, December 2024, and July 2024, respectively. The average of their predicted peak values is 114.7 ± 22.3.

ii) Quassim, Attia, and Elminir (2007) used a neuro fuzzy approach to predict Solar Cycle 25. According to their study the cycle maximum would have an amplitude of 116 around 2021.

iii) Okoh et al. (2018) used a method known as Hybrid Regression-Neural Network that combines regression analysis and neural network learning (the Ap index is used for prediction) to forecast the amplitude of Solar Cycle 25. They predicted a peak amplitude of 122.1 ± 18.2 occurring on January 2025 ± 6.

iv) Attia, Ismail, and Basurah (2013) used a neural network model and found a suitable number of network inputs for the sunspot data series based on sequential forward search for the neuro-fuzzy model. This study predicted a peak SSN of 90.7 ± 8 on 2022.

v) Covas, Peixinho, and Fernandes (2019) used a neural network technique to perform a spatio-temporal analysis of solar cycle data and estimated the maximum SSN for Solar Cycle 25 to be 57 ± 17 occurring on 2022-2023.

4.7. Uncategorized Forecasts

i) Chistyakov (1983) used regularities of secular and 22-year variations for their forecast. They predict a peak SSN of 121 occurring in 2028.5.

ii) Kontor et al. (1984) utilized a hypothesis that the cycle peak envelop oscillates between the time dependent high and low levels to predict the nature of Solar Cycle 25. They estimated a peak SSN of 117 around 2024.

4.8. Analysis of Solar Cycle 25 Forecasts

In Figure 4 various predictions for Solar Cycle 25 are represented. For reference, the gray-dashed line indicates the observed peak amplitude of Solar Cycle 24 (113.3 SSN). A perusal of Figure 4 and Table 1 indicates that forecasts for Solar Cycle 25 based on different techniques still diverge widely, with a majority of the forecasts indicating that Solar Cycle 25 would be stronger than Solar Cycle 24. The mean (± 1σ) of the different predictions is 136.2 ± 41.6 which nonetheless conforms to a climatological weak cycle keeping in mind the definition of cycle strengths based on observed cycle amplitudes over the past 100 years (see Figure 1). We note that there are far fewer forecasts for Solar Cycle 25—approximately half—than there were for Solar Cycle 24; this in itself is encouraging and perhaps indicative of the realization that playing Russian roulette with solar cycle forecasting is perhaps not the best of ideas.
Figure 5  Comparison of physical model based predictions for the strength of Solar Cycle 24 (left) and Solar Cycle 25 (right). Both predictions for Solar Cycle 24 were based on dynamo models. Predictions for Solar Cycle 25 completely relying on physics-based magnetic field evolution models (imbibing physics of SFT as well as dynamo models) are indicated in blue. Predictions based on a combining SFT model based estimates of polar field with empirical precursor techniques are depicted in red. For Solar Cycle 24, the mean $(\pm 1\sigma)$ of the two physics-based predictions is $177.0 \pm 62.6$ SSN. For the four physics-based predictions of Solar Cycle 25 the mean $(\pm 1\sigma)$ is $110.5 \pm 13.5$ SSN. The horizontal dotted lines in both panels denote the observed Solar Cycle 24 peak amplitude (113.3 SSN) for comparison. Clearly, for Solar Cycle 25, there is a convergence among physics-based predictions. All numbers are in the scale of the new, revised sunspot time series. Details of the utilized methodologies can be found in the references cited below the corresponding predictions.

On a more serious note, we now delve deeper into physics-based forecasts for Solar Cycle 25 to ascertain whether any meaningful progress has occurred in this front. While these are part of the “confusogram” of Solar Cycle 25 forecasts based on diverse techniques (Figure 4), we extract them out and analyze them separately in the next section.

4.9. Comparative Assessment of Physics-Based Predictions of Solar Cycles 24-25

In Figure 5 (left), we compare those physical model based predictions of Solar Cycles 24 and 25 which explicitly predicted peak SSNs (as opposed to qualitative forecasts such as weak or moderate or strong cycles). We estimate the mean $(\pm 1\sigma)$ of the physics-based predictions for Solar Cycle 24 to be $177.0 \pm 62.6$ (SSN). This mean is much larger than what was observed (113.3 SSN) and the standard deviation is indicative of a large divergence.

There were four distinct physical model based forecasts for Solar Cycle 25 which are depicted in Figure 5 (right). Two of these models (Upton and Hathaway, 2018; Jiang et al., 2018) utilized different methodologies for simulating the evolution of the Sun’s surface radial fields. They predicted the polar field expected at the end of Solar Cycle 24 and utilized the observed relationship between the polar field and the subsequent cycle amplitude (i.e., a calibrated precursor method) to forecast the peak of Solar Cycle 25.

Bhowmik and Nandy (2018) utilized an SFT model calibrated over a century by assimilating the observed statistics of emergence of bipolar sunspot pairs to simulate the evolution of the Sun’s surface radial field and polar flux. This was coupled to a solar dynamo model which assimilated the data from the SFT model at every solar minima. Using this methodology they first predicted the polar field expected at the minimum of Solar Cycle 24 (in
effect 4 years in advance) and subsequently utilized the century-scale dynamo simulation to forecast Solar Cycle 25. The Bhowmik and Nandy (2018) century-scale data driven solar dynamo simulation reasonably matched past solar cycles (except the extreme Cycle 19) and predicted a weak Solar Cycle 25 similar or slightly stronger than Solar Cycle 24. This is the first attempt at a solar cycle forecast that is based on century-scale calibrated, data driven simulations which shows promise in other contexts as well (Jiang et al., 2013). Labonville, Charbonneau, and Lemerle (2019) used a slightly different methodology of coupling an SFT and dynamo model in which the two models communicated more frequently with each other; they predicted a Solar Cycle 25 which is much weaker than Solar Cycle 24.

For the four physics-based predictions of Solar Cycle 25 the mean predicted amplitude ($\pm 1\sigma$) is 110.5 $\pm$ 13.5 (SSN), i.e., very similar to the observed peak of the recently concluded Solar Cycle 24.

Independently, the four physics-based forecasts for Solar Cycle 25 are not too distinct from each other in the sense that all predict a climatological weak sunspot cycle. More importantly, there is a small range over which the predicted uncertainties (or range of forecasts) agree. Taken together, and compared to the physics-based forecasts for Solar Cycle 24, the physics-based Solar Cycle 25 forecasts indicate significant progress towards a convergence (or a “consensus forecast”). Is this accidental or is this convergence of predicted numbers for Solar Cycle 25 indicative of a convergence of fundamental ideas related to the solar dynamo mechanism? We explore this important question in the next section.

5. Advances in Understanding Solar Cycle Predictability

The solar dynamo mechanism is believed to operate throughout the Sun’s convection zone (and up to its surface layers) wherein, differential rotation, turbulent convection and large-scale plasma flows such as meridional circulation, turbulent flux pumping (Hazra and Nandy, 2016) play important roles in induction and transport of magnetic fields (see, e.g., Figure 6). Following the pioneering work of Parker (1955a), there has been a community wide consensus that the toroidal component of the Sun’s magnetic field is generated by the stretching of poloidal field lines by the solar differential rotation in the solar convection zone (SCZ). We note that observations and simulations of magnetic activity in other stars also bear out the importance of stellar differential rotation and their variations in the sustenance of magnetic cycles and in explaining the observed rotation-activity relationship (Nandy, 2004; Brun et al., 2015).

The toroidal flux tubes rise up due to magnetic buoyancy (Parker, 1955b) during which they are twisted by helical turbulent convective motions, which are thought to sustain a mean-field $\alpha$-effect that can reproduce the Sun’s poloidal field (Parker, 1955a). This process remains unobserved and unconstrained till date. Simulations of the dynamic rise of magnetic flux tubes through the SCZ show that the Coriolis force can impart a systematic tilt to bipolar sunspot pairs (D’Silva and Choudhuri, 1993; Fan, Fisher, and Deluca, 1993), which explains the observed Joy’s law for active region tilt angles (Hale et al., 1919). Babcock (1961) and Leighton (1969) suggested that the decay and dispersal of these tilted bipolar sunspot pairs can regenerate the Sun’s large-scale poloidal (dipolar) field (Figure 6) mediated via flux transport processes providing an alternative formulation to the mean-field $\alpha$-effect. This alternative formulation came to be known as the Babcock–Leighton (hereafter B-L) dynamo mechanism (Nandy and Choudhuri, 2001)—a process in which near-surface flux transport processes play a critical role in the build-up and reversal of the Sun’s large-scale dipolar field (of which the observed surface radial field is a proxy). This process is observed in action on
Figure 6  Artistic rendering of a solar dynamo simulation. A cutout of the solar interior reveals the solar convection zone. The dynamo generated toroidal component of the magnetic field which forms sunspots is represented in the right-hand meridional plane (opposite polarities denoted in red and blue). The dynamo generated poloidal component of the magnetic field is represented in the left-hand meridional plane (in green). The poloidal component is approximately dipolar at this phase of the simulation (near solar minimum). The right-hand meridional plane shows that the toroidal field of the next cycle is already being inducted at high latitudes from this dipolar field component of the previous cycle. Credits: Simulation data by Nandy, Muñoz-Jaramillo, and Martens (2011) and rendering by Tom Bridgman; NASA Scientific Visualization Studio.

the Sun’s surface. Numerous flux transport dynamo models have been built based on the Babcock–Leighton mechanism with different levels of complexity (Durney, De Young, and Roxburgh, 1993; Durney, 1995; Choudhuri, Schussler, and Dikpati, 1995; Dikpati and Charbonneau, 1999; Nandy and Choudhuri, 2001, 2002; Muñoz-Jaramillo, Nandy, and Martens, 2009; Muñoz-Jaramillo et al., 2010; Hazra and Nandy, 2016; Kumar, Jouve, and Nandy, 2019), which reasonably match various solar cycle properties.

Nevertheless, for long there has been no consensus on which of these two mechanisms (mean-field $\alpha$-effect of the BL process) for poloidal field generation plays a predominant role in the dynamo mechanism. The resolution to this dilemma is fundamental because the dominant poloidal source is also likely to be the primary source of variability in the solar magnetic cycle and the ability to adequately model this variability is fundamental to predictive models of the sunspot cycle.

Careful analysis of long-term solar cycle observations relating the tilt and flux content of solar active regions (i.e., the BL source term) to the strength of the next sunspot cycle clearly implicates the BL mechanism as the primary determinant of solar cycle amplitudes (Dasi-Espuig et al., 2010). Fundamental theoretical analysis without recourse to parameterizations suggests that the surface magnetic field distribution related to the BL mechanism must be the primary source to the internal induction of the toroidal field (Cameron and Schüssler, 2015). Surface flux transport simulations imbibing the BL mechanism are able to reproduce the observed evolution of the Sun’s large scale polar fields (Jiang et al., 2014). Coupled models of magnetic field evolution on the solar surface and in the convection zone (i.e., STF and dynamo models) successfully explain a century of solar cycle observations (Bhownik and Nandy, 2018). These observations and theoretical simulations leave little doubt that the primary source for the Sun’s poloidal field and the basis of cycle to cycle variability is
The Babcock–Leighton solar dynamo mechanism driven by the emergence and dispersal of tilted bipolar sunspot pairs mediated via near-surface flows; anyone who believes otherwise is ignoring evidence—a fundamental tenet of the scientific process.

However, both the dynamo models that were utilized for predictions of Solar Cycle 24—and whose predictions diverged widely—were based on the BL mechanism. Does this go against the emergent understanding that the BL dynamo mechanism is the major source of variability in the solar magnetic cycle? Yeates, Nandy, and Mackay (2008) and Karak and Nandy (2012) demonstrated that the BL dynamo model behaves very differently under different assumed flux transport scenarios and that the relative efficacy of turbulent diffusion, meridional circulation, and turbulent pumping determines the dynamical memory of the dynamo which is fundamental to predictability. Yeates, Nandy, and Mackay (2008) argued that differing assumptions related to the dominant flux transport mechanisms in the Dikpati, de Toma, and Gilman (2006) and Choudhuri, Chatterjee, and Jiang (2007) predictive models resulted in the discrepancy in their predictions.

Furthermore Yeates, Nandy, and Mackay (2008) and Karak and Nandy (2012) utilized stochastically fluctuating source terms in a non-linear BL dynamo model to estimate correlations between the polar field at cycle minima and subsequent cycle strengths and established that efficient transport of magnetic flux by turbulent diffusion and pumping in the SCZ reduces the dynamical memory of the sunspot cycle to only one cycle (see Figure 7). This implies that solar cycle predictions are only possible one cycle in advance, and that the polar field at cycle minima contributes only to the strength of the next sunspot cycle.

The theoretical hypothesis of this short one cycle memory in the dynamo mechanism was soon confirmed in an analysis of the relationship between polar flux and the amplitude of different cycles by Muñoz-Jaramillo et al. (2012). Following their approach, we perform an analysis of the relationship between solar flux (estimated from flux calibrated faculae count) and the peak sunspot number of different cycles. This analysis, based on the revised sunspot time series is presented in Figure 8.
Figure 8 Observed cycle to cycle correlations between the polar flux at cycle minima (say, \( n \)) and the cycle amplitude of different cycles, namely (a) cycle \( n \), (b) cycle \( n + 1 \), (c) cycle \( n + 2 \), and (d) cycle \( n + 3 \). The orange filled circles represent the analysis carried out using average polar flux (derived from polar faculae) and cycle amplitude, whereas the cyan filled circles show the relationship between the average dipole moment (scaled appropriately to place them in the figure) and solar cycle amplitude. The numbers inside the circles indicate the corresponding solar cycle numbers. For average dipole moment calculations we have used polar field data from the Wilcox Solar Observatory (WSO). The only significant correlation recovered is between the polar flux at the minima of a cycle, say \( n \) and the amplitude of the next cycle \( n + 1 \) as evident in panel (b).

on the BL mechanism with fluctuating poloidal source term (Figure 7) and observed solar cycle correlations (Figure 8), we see that the toroidal flux of a cycle is not correlated with the poloidal flux measured near the poles at the end of that cycle. This indicates that the poloidal field source is stochastic (imbibing random variations) and the link of predictability is broken from the toroidal field to the poloidal field conversion process in the dynamo cycle. However, we find that these long-term statistically significant observations confirm the existence of a correlation between the polar field at the minima of a cycle \( n \) and the cycle amplitude of the next cycle \( n + 1 \). This relationship is causally explained on the basis of the dynamo theory, which we have established earlier, and provides the basis for
### Table 1

A list of predictions for Solar Cycle 25 by different groups using diverse methods.

| Authors | Predicted SSN | Time       | Category |
|---------|---------------|------------|----------|
| Chistyakov (1983) | 121 | 2028.5 | – |
| Kontor et al. (1984) | 117 | 2024 | – |
| Quassim, Attia, and Elminir (2007) | 116 | 2021 | ML/NN |
| Javaraiah (2015) | 50 ± 10 | – | SP |
| Li, Feng, and Li (2015) | 109.1 | Oct 2023 | S |
| Pishkalo (2008) | 112.37 ± 33.4 | 2023.4 ± 0.7 | S |
| Li et al. (2018) | 168.5 ± 16.3 | Oct 2024 | S |
| Singh and Bhargava (2017) | 102.8 ± 24.6 | June 2024 | S |
| Gopalswamy et al. (2018) | 148 | – | P |
| Helal and Galal (2013) | 118.2 | 2022-2023 | P |
| Pesnell and Schatten (2018) | 135 ± 25 | 2025.2 ± 1.5 | P |
| Bhowmik and Nandy (2018) | 118 | 2024 ± 1 | MB |
| Labonville, Charbonneau, and Lemerle (2019) | 89±29 / 14 | 2025.3±0.89 / 1.05 | MB |
| Upton and Hathaway (2018) | 110 | – | MB |
| Sarp et al. (2018) | 154 ± 12 | 2023.2 ± 1.1 | N |
| Han and Yin (2019) | 228.8 ± 40.5 | 2023.918 ± 1.64 | S |
| Kakad, Kumar, and Kakad (2020) | 143.8±25 | – | S |
| Sello (2019) | 107 ± 10 | July 2023 ± 1 | N |
| Okoh et al. (2018) | 122.1 ± 18.2 | January 2025 ± 6 | ML/NN |
| Kane (2007b) | 112 to 127 (mean 119) | 2022-2023 | SP |
| Du and Du (2006) | 111.6 ± 17.4 | – | S |
| Attia, Ismail, and Basurah (2013) | 90.7 ± 8 | 2022 | ML/NN |
| Jiang et al. (2018) | 125 ± 32 | – | MB |
| Covas, Peixinho, and Fernandes (2019) | 57 ± 17 | 2022-2023 | ML/NN |
| Rigozzo et al. (2011) | 132.1 | April 2023 | SP |
| Hawkes and Berger (2018) | 117 | – | P |
| Petrovay et al. (2018) | 130 | Late 2024 | P |
| Kitiashvili (2020) | 50 ± 15 | 2024-2025 | N |
| Hiremath (2008) | 110 ± 11 | 2023 | S |
| Dani and Sulistiani (2019) | 114.7±22.3 / 23.2 | Sep 2024 | ML/NN |
| Hathaway and Wilson (2004) | 70 ± 30 | 2023 | S |
| Abduhasamatov (2007) | 50 ± 15 | – | S |
| Hazra and Choudhuri (2019) | 140.5 ± 2.5 | – | P |
| McIntosh et al. (2020) | 229 ± 76 | – | P |

1S: statistical/correlation analysis, P: precursor technique, MB: model based, N: non-linear techniques, ML/NN: machine learning or neural network method, SP: spectral method.

2The predicted SSN is the mean of their four predictions using different machine learning classifiers. The error bar is chosen to include the maximum range of the predictions.

predictive solar dynamo models and precursor prediction techniques—explaining why the latter tend to be more accurate than other solar cycle prediction methods.

Other than randomness in the poloidal source or stochastic fluctuations in dynamo transport parameters, magnetic buoyancy considerations (Nandy, 2002), non-linear Lorentz feed-
back mechanisms on plasma flows and dynamo sources (Muñoz-Jaramillo, Nandy, and Martens, 2010; Wilmot-Smith et al., 2005), time delay effects (Wilmot-Smith et al., 2006) magnetically modulated plasma flows (Lekshmi, Nandy, and Antia, 2018, 2019) may cumulatively contribute to cycle strength fluctuations and asymmetries in the sunspot cycle (Jiang et al., 2014; Shetye, Tripathi, and Dikpati, 2015) and in the polar field strength (Bhowmik, 2019). Such fluctuations that spawn asymmetry can often lead to long-term activity modulation including extreme episodes such as grand maxima and minima (Hazra, Passos, and Nandy, 2014; Passos et al., 2014) and changes in the global parity of dynamo solutions (Hazra and Nandy, 2019). The extent to which the solar dynamo output variation is influenced by stochastic or deterministic chaotic modulation is a subject of active debate (Mininni, Gómez, and Mindlin, 2002; Mininni et al., 2004; Bushby and Tobias, 2007). It is expected that improved understanding of the interplay between randomness in dynamo source terms, fluctuations in flux transport processes and non-linear feedback mechanisms may lead to more precise understanding of long-term solar activity fluctuations beyond cycle predictions.

6. Resolution of Outstanding Questions in Solar Cycle Predictions

Finally, we summarize below resolutions to some outstanding questions in solar cycle predictions that were a challenge to the community about a decade back. These resolutions reflect the advances in our understanding of the physics of solar cycle predictability in the intervening period from the minimum of Solar Cycle 23 to the minimum of Solar Cycle 24 and lays the basis for future efforts in forecasting solar cycles.

i) Is it possible to predict the sunspot cycle?

Based on numerical simulations with stochastic and deterministic non-linear dynamo models Bushby and Tobias (2007) argued that the solar cycle is not predictable. Their conclusion was based on solutions to the non-linear system of equations diverging over large timescales when slightly different initial conditions were assumed. That solutions in non-linear dynamical systems would diverge over large timescales was well known, however, in the weather community and was demonstrated about half a century back in the pioneering work by Lorenz (1963). However, it is our considered view that Bushby and Tobias (2007) over-interpreted their results (or erred on the side-of-caution) to generalize their conclusion to imply that sunspot cycle predictions are simply not possible (not even on short timescales). Numerous simulations with stochastically forced, non-linear dynamo models and observational analysis have since indicated that short-term predictions of the upcoming solar cycle are possible based on a causal relationship between the Sun’s polar field and the toroidal field of the next sunspot cycle (Yeates, Nandy, and Mackay, 2008; Dasi-Espuig et al., 2010; Karak and Nandy, 2012; Muñoz-Jaramillo et al., 2012; Bhowmik and Nandy, 2018; Jiang et al., 2018). Thus, based on the evidence of this research work, we reiterate that short-term, one cycle forecast (at least of climatological relevance) is indeed possible.

ii) What is the best proxy for solar cycle predictions?

Theory of the solar dynamo mechanism (Cameron and Schüssler, 2015), numerical dynamo simulations (Yeates, Nandy, and Mackay, 2008; Karak and Nandy, 2012; Bhowmik and Nandy, 2018), and analysis of long-term observations (Dasi-Espuig et al., 2010; Muñoz-Jaramillo et al., 2012) indicate that the best proxy for solar cycle predictions is the polar field (flux) at the minimum of the previous cycle. There is
a causal relationship between the polar flux at cycle minima (which is a measure of the poloidal field strength) and the sunspot cycle amplitude (which is a measure of the underlying toroidal field) as the former acts as the source of the latter. Thus precursor-technique-based predictions that use direct polar field measurements or its proxy to predict the sunspot cycle are physically well founded. Note that after the cycle has already started, the Waldmeier effect relating the growth rate to the cycle amplitude may also serve as a reliable, albeit short-term, precursor forecasting approach.

iii) **How early can we predict the sunspot cycle?**
A good idea of the polar field at sunspot cycle minima is necessary to predict the next sunspot cycle. Typically, therefore, predictions made with accurate knowledge of the polar field strength at minima are likely to be more accurate. However, solar STF models can be used with synthetic input profiles of the declining phase of a cycle to predict in advance the polar field strength at the minimum of that cycle; this predicted polar field can be utilized in precursor methods (Jiang et al., 2018) or dynamo models of the solar cycle (Bhowmik and Nandy, 2018) to predict the next sunspot cycle. Such methodologies therefore can extend the prediction window of a cycle, say cycle \([n + 1]\), to a few years before the minima of cycle \([n]\); this window may be stretched to at most 10 years based on our current understanding.

iv) **How many cycles into the future can we predict?**
Theoretical simulations exploring the dynamical memory of the sunspot cycle based on dynamo simulations show that the polar field at the minima of cycle \([n]\) is causally related to the toroidal field of the next, i.e., \([n + 1]\) cycle only (Yeates, Nandy, and Mackay, 2008; Karak and Nandy, 2012) when turbulent flux transport processes dominate in the solar convection zone (see Figure 7). We note that accounting for the existence of mean-field dynamo \(\alpha\)-effect which provides a basal level dynamo-action in the convection zone in the presence of the more dominant BL source (Hazra, Passos, and Nandy, 2014; Passos et al., 2014) may lead to further complexities in persistence of cycle to cycle memory (Hazra, Brun, and Nandy, 2020); but this consideration still limits the predictability to one cycle. The motivation for stochastic fluctuations in the BL source in the above theoretical simulations arise from the randomness in the tilt-angle distribution of bipolar sunspot pairs—which is fundamental to limiting the window of predictability. Long-term observations (Muñoz-Jaramillo et al., 2012) of solar activity correlations confirm this (see Figure 8). Therefore, we postulate that the dynamical memory of the solar cycle—as far as cycle to cycle variations are concerned—is short. Reasonably accurate predictions are possible only for the next sunspot cycle, and not beyond.

v) **What properties of the solar cycle can we predict?**
The strength of the sunspot cycle as well as its timing can be approximately predicted. For example, Bhowmik and Nandy (2018) predicted the complete profile of Sunspot Cycle 25 based on a combination of a solar STF model and a solar dynamo model. Because the strength of a sunspot cycle is related to its rate of rise, the latter can also in fact be a byproduct of solar cycle predictions.

vi) **What physical dynamo model of the solar cycle is best suited for predictive purposes?**
Recent progress in solar dynamo theory and modeling, and observational evidence together, indicate that the Babcock–Leighton mechanism for poloidal field generation is the primary source of variability in the solar cycle (Dasi-Espuig et al., 2010; Cameron and Schüssler, 2015; Bhowmik and Nandy, 2018). These models can also be constrained by observations and driven by data assimilation. Philosophically and logically therefore, solar dynamo models based on the Babcock–Leighton framework should be utilized for predictive purposes.
vii) Has convergence been achieved in physics-based solar cycle predictions for Sunspot Cycle 25?

Yes, based on our analysis we conclude that physics-based forecasts for Solar Cycle 24 have converged and agreed with each other with minor differences (Figure 5). These differences may result from disparate modeling techniques and (or) data assimilation methodologies. Our analysis reveals the physics-based predictions of Solar Cycle 25—based on the Babcock–Leighton solar dynamo framework—predict a weak to moderate–weak Solar Cycle 25 from the climatological perspective. Considering the range of uncertainty in some of the physics-based ensemble forecasts, a reasonable “consensus” derived from these models would be that Sunspot Cycle 25 would be a weak or moderate–weak cycle peaking around 2024–2025. We note that Solar Cycle 25 forecasts based on alternative approaches that do not rely on physics-based models continue to diverge significantly.

viii) With what accuracy can we predict the solar cycle?

Some uncertainties in prediction are bound to result from the many uncertainties and parameterizations involved in modeling. Models that make early predictions are perhaps prone to larger uncertainties because of the higher probability of statistically extreme fluctuations, e.g., appearance of anomalous active regions (Nagy et al., 2017) in the intervening prediction window. However, some of the physical model-based predictions can account for reasonable uncertainties through ensemble forecasts that provide a range of values for the predicted amplitude of the solar cycle (Bhowmik and Nandy, 2018; Jiang et al., 2018; Labonville, Charbonneau, and Lemerle, 2019). Determination of uncertainties in forecast and therefore generating a possible range of forecast values is expected to gain some attention in the future as data driven, model-based forecasts of the solar cycle are further refined.

ix) What is the best approach to achieving a “consensus forecast” by any solar cycle prediction panel?

A large number of solar cycle forecasts utilizing a large number of (non-physics based) techniques resulting in greater divergence indicates a statistical reality rather than an informed scientific debate of equally viable ideas. This is well established in our comparative analysis of predictions for Solar Cycles 24 and 25. The path towards generating a consensus expectation for the upcoming cycle by any solar cycle prediction panels—such as the NOAA-NASA Prediction Panel—is therefore challenging. Based on our analysis of the progress in solar cycle predictions, we suggest a more scientifically motivated pathway towards generating a “consensus forecast”. Such panels must consider the underlying physics of solar cycle predictability and seriously assess only those methods—and their agreement or disagreement—which are rooted in firm physical foundations. It is clear from our analysis that while predictions for Solar Cycle 25 (Figure 4) utilizing diverse techniques still suffer from non-convergence just like Solar Cycle 24 forecasts (Figure 3), physically well founded model-based predictions for Sunspot Cycle 25 have converged (Figure 5); however, this does not imply future physical model based forecasts would always agree with each other. Thus the basis of the consensus—or any disagreement—must be clearly declared for the community to understand and appreciate the subtleties involved in the generation of the consensus. Although widely in use, statistical averages of independent forecasts (that are under consideration) in order to arrive at an exact numerical value for the peak sunspot number should be avoided; a more prudent approach is to generate a climatological forecast, i.e., weak, moderate, strong etc., based on the various numerical predictions and their uncertainties. Consensus on the timing of the peak and length of cycles can
however be more quantitative as long as uncertainty ranges are clearly established. Finally, the research manuscripts that have contributed to the consensus statement must be disclosed. On the one hand, this allows independent scrutiny and analysis by the community, and on the other hand this provides due credit to the researchers whose work inform and contribute to solar cycle predictions, given that the panel itself is not involved in any technical (peer-reviewed) research leading to a “consensus forecast”. Implementation of these recommendations would lead to a relatively more rigorous, transparent and inclusive process for achieving a meaningful consensus expectation of the strength of future solar cycles.

7. Concluding Remarks

In summary, here we review predictions of Sunspot Cycles 24-25 from different groups based on diverse techniques and perform a comparative analysis of these predictions. Our analysis reveals that while predictions based on diverse techniques continue to disagree across Sunspot Cycles 24-25, physical model based forecasts for Solar Cycle 25 have converged. This convergence indicates a weak to moderately weak Sunspot Cycle 25. We argue that this convergence in physics-based predictions is a consequence of the convergence of ideas and new insights on the physical underpinnings of the solar dynamo mechanism. In particular, we note there is now overwhelming evidence that the Babcock–Leighton mechanism is the dominant driver of solar cycle variability on decadal timescales and that the dynamical memory of the solar dynamo mechanism is short, allowing for predictions of only the next sunspot cycle.

Based on our analysis, we suggest a more rigorous pathway for generating a “consensus forecast” for future sunspot cycles by panels—such as the NASA-NOAA Prediction Panel—which do not perform any independent technical research for a forecast, but attempt the challenging task of reviewing and making sense of a multitude of different published forecasts.

Following the early disagreement and controversies related to Solar Cycle 24 predictions, significant progress has been achieved in the intervening decade, between the minimum of Solar Cycle 23 and Solar Cycle 24. This progress is presented and discussed in the light of resolutions to many outstanding questions related to solar cycle predictability. It is our hope that this progress would lay the foundations of more accurate, physics-based predictive models of the sunspot cycle on the one hand, and on the other hand, more usefully constrain the fundamental physics of solar and stellar magnetic cycles.

Acknowledgements This review is dedicated to the memory of Bernard Durney who passed away in 2019 somewhere in the South of France, his last years spent in relative seclusion far away from the solar physics community. Bernard made fundamental contributions to the development of dynamo models of the solar cycle based on the Babcock–Leighton idea, including elucidating the role of meridional circulation in the near-surface evolution of the Sun’s large-scale dipolar magnetic fields. I first started corresponding with him as a PhD student from India and I am indebted to him for his generosity in sharing his knowledge and debating ideas with someone he had never met. In fact, although we corresponded for many years, I never got a chance to meet him in person. I am indebted to many of my students and collaborators who have contributed to my journey of exploring the physics of the sunspot cycle, particularly towards understanding the basis of solar cycle predictability. I am grateful to Soumyaranjan Dash and Shaonwita Pal for assistance with literature survey and preparation of some of the figures. I acknowledge utilization of data from the NASA/SDO HMI instrument maintained by the HMI team, the Royal Greenwich Observatory/USAF-NOAA active region database compiled by David H. Hathaway and MWO calibrated polar faculae data from the solar dynamo database maintained by Andrés Muñoz-Jaramillo. I acknowledge utilization of the hemispheric polar field data obtained by J. Todd Hoeksema and many dedicated graduate students at Stanford University’s
Wilcox Solar Observatory. The Wilcox Solar Observatory is currently supported by NASA. I acknowledge usage of the yearly mean sunspot number data from the Solar Influences Data Analysis Centre (SILSO, Royal Observatory of Belgium, Brussels) and useful discussions with Frédéric Clette on the revised sunspot time series. Much of the understanding related to the solar magnetic cycle and its predictability has resulted from confronting theoretical dynamo models with these long-term solar activity databases and the continued sustenance of these databases cannot be overemphasized. This work benefited from discussions with colleagues under the aegis of the VarSITI Solar Evolution and Extrema program of SCOSTEP and the ISWAT cluster on Long-term Solar Variability under the aegis of COSPAR’s Panel on Space Weather. The Center of Excellence in Space Sciences India (CESSI) is funded by the Ministry of Education, Government of India, under the Frontier Areas of Science and Technology (FAST) scheme. Finally, I am grateful to the solar physics community of Argentina, its wonderful people and the beautiful music of tango, all a source of inspiration during my sabbatical visit to that country in connection with the 2019 total solar eclipse—during which the idea and early work for this review was initiated.

Disclosure of Potential Conflicts of Interest  The author declares no conflicts of interest.

Publisher’s Note  Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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