On the Strength and Duration of Solar Cycle 25: A Novel Quantile-Based Superposed-Epoch Analysis

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Abstract
The sunspot number (SSN) is an important – albeit nuanced – parameter that can be used as an indirect measure of solar activity. Predictions of upcoming active intervals, including the peak and timing of solar maximum, can have important implications for space-weather planning. Forecasts for the strength of Solar Cycle 25 have varied considerably, from being very weak to one of the strongest cycles in recorded history. In this study, we develop a novel quantile-based superposed-epoch analysis that currently predicts that Solar Cycle 25 will be very modest (within the lowest 25th percentile of all numbered cycles), with a monthly averaged (13-month average) peak of ≈ 130 (110) likely occurring in December 2024. We validate the model by performing retrospective forecasts (hindcasts) for the previous 24 cycles, finding that it outperforms the baseline (reference) model (the “average cycle”) 75% of the time.

Keywords Solar-cycle prediction · Space weather · Sunspot number · Statistical analysis

1. Introduction
Solar activity manifests itself in the sunspot cycle, a roughly 11-year change in the number of observed sunspots on the solar surface. These variations correlate well with other measures of activity, such as coronal mass ejections, solar flares, solar energetic particles (SEPs), as well as radiation. This 11-year modulation represents one-half of the 22-year Hale cycle, which follows the complete reversal of the solar magnetic field back to its original polarity. Although an imprecise measurement of activity, the sunspot number (SSN) is perhaps the longest, continuously measured parameter and, thus, provides a unique glimpse into the long-term variations of the Sun. At least indirectly, it provides a measure of the complexity of the photospheric magnetic field, particularly the number of active regions visible on the solar disk.

The properties and evolution of the solar cycle have been extensively reviewed by Hathaway (2015). Focusing on variations over the last ∼ 270 years or so, we note that the relevant variations include: i) the Gleissberg cycle – an 80 – 90-year variation in the amplitudes of the
cycles (Gleissberg, 1939); ii) the Gnevyshev–Ohl effect – a two-cycle variation with odd-numbered cycles having a higher peak than the preceding even-numbered cycle (Gnevyshev and Ohl, 1948); and iii) a general overall increase from Cycle 1 through to the present (Wilson, 1988). Applying these rules heuristically to Cycle 25: i) The Gleissberg cycle suggests that Cycle 23 or 24 occurred at a minimum; thus, the peak for Cycle 25 should be modestly larger; ii) the Gnevyshev–Ohl effect suggests that Cycle 25 should be modestly larger than the Cycle 24 peak; and iii) the secular increase since Cycle 1 also suggests that Cycle 25 should peak slightly higher than Cycle 24. To these heuristics, we can add a further: large swings in peak values do not occur from one cycle to the next. That is, the largest peaks over the last 270 years are built upon the superposition of these three modulations. Thus, it seems reasonable, although arguable, to infer that any prediction should be constrained such that it does not vary substantially from the previous one (with Cycles 4 – 5, 7 – 8, 19 – 20 do not fit this pattern).

The International Sunspot number, which is also referred to as the Wolf, Zurich, or relative SSN, is a parameter combining the number of sunspots and groups of sunspots. The SSN is computed daily using the following expression:

\[
R = k(10g + s),
\]

where \(s\) is the number of individual spots, \(g\) is the number of sunspot groups, and \(k\) is a factor that varies with location and instrumentation (Clette et al., 2014).

Over the last ten years, SSN has been revised in several significant and, in some cases, controversial ways. The details are not directly relevant to the present study, so our analysis could be applied equally well to any variant. We do not anticipate that there would be any substantial changes to our results or interpretation, although this would require verification. The most widely used dataset is the Sunspot Index and Long-term Solar Observations (SILSO) provided by the Solar Influences Data analysis Center (SIDC), a department of the Royal Observatory of Belgium, and this is the dataset that we use in the present study.

Solar-cycle prediction techniques can be broadly separated into two classes: Those attempting to predict an ongoing cycle, and those predicting a future cycle that has not yet begun (Hathaway, 2015). The former is conceptually more straightforward, and, given the data available to constrain the fit, should always return estimates that are more accurate than the latter. Generally, the techniques applied to predicting an ongoing cycle are empirical in nature, such as regression approaches. In this study, we develop a method that requires the cycle to have already begun.

Several reviews have discussed the many approaches of making solar-cycle predictions, for example, reviewed and analyzed 75 predictions of the amplitude for Solar Cycle 24, revisiting the topic in subsequent years to assess the accuracy of these predictions (e.g. Pesnell, 2020). In general, precursor models performed better than climatological models. Embedded within a more general review of the solar cycle, Hathaway (2015) described the main types of solar-cycle prediction models, suggesting that statistical methods generally performed “only marginally” better than a baseline model relying on the properties of the average cycle. Most recently, Petrovay (2020) discussed the subset of predictions that were, in principle, related to dynamo theory and further restricted the subset to those that predicted the amplitude of the next maximum before the start of that cycle. Predictions for Solar Cycle 25 were summarised recently by Nandy (2021), who concluded that the maximum amplitude for Cycle 25 was 136.2 ± 41.6. This agreed reasonably well with the consensus prediction from the Solar Cycle 25 Prediction Panel (SC25PP), an international group of scientists, who had earlier published a preliminary forecast of 114.6 ± 10.0, anticipated to
occur in July 2025. These values, however, are in stark contrast to a prediction by McIntosh et al. (2020), who argued that Cycle 25 would be one of the strongest cycles in recorded history. Their initial estimate of 233 (68% Confidence Intervals (CIs): 204–254) was later updated to a value of 190. More recently, and supporting this position, Prasad et al. (2022) used a deep-learning technique to suggest that Cycle 25 will peak at 172 in August 2023. In contrast, Kumar, Biswas, and Karak (2022) exploited the Waldmeier effect, that is, the observation that the rise time of a sunspot cycle varies inversely with the cycle amplitude and a physical link with the buildup of the previous cycle’s polar field after its reversal, to infer that the peak of Cycle 25 will only be slightly higher than that of Cycle 24. Clearly, as Cycle 25 progresses, the forecasts have not (yet) converged to a single, consensus prediction.

While the previous studies generally provided long-term forecasts, that is, prior to the commencement of the cycle being forecasted, another class of forecasts focuses on medium-term solar-activity forecasting, typically several months to a year or two ahead. One of the earliest was that by McNish and Lincoln (1949), who predicted that the future value in a cycle was the mean of all past values for that part of the cycle, with a correction dependent on the difference of the earlier values of the cycle from the mean cycle. Refinements to this approach have been made over the years (e.g. Boykin and Richards, 1966; Niehuss, Euler, and Vaughan, 1996; Suggs, Euler, and Smith, 2013), and most recently, by Petrova et al. (2021), who added an adaptive Kalman filter to improve accuracy and reduce uncertainties.

In this study, we develop a simple but intuitive technique for predicting the likely evolution of the current solar cycle once it is underway. Given its statistical nature, this approach is similar to the medium-term forecasts in that it is only applicable once the cycle has begun; however, the prediction window stretches out further in time until the completion of the cycle. In this initial study, our primary aim is to present the technique, noting that it reproduces reasonable results, consistent with most previous predictions, and in contrast to some of the more extreme predictions of McIntosh et al. (2020) and Prasad et al. (2022). We do not suggest that the proposed technique performs any better than many of the previously developed statistical and physics-based models that already exist. Instead, we suggest that it serves to complement many of these techniques. More importantly, it allows us to make several inferences from it. The degree to which this new model outperforms other schemes will be the subject of a follow-on study.

We develop the article as follows: We begin by summarising the data used to drive the prediction, then discuss the modeling approach we have developed. After this, we describe how the technique is applied to Cycle 25. Next, we assess the technique by performing retrospective forecasts of the previous 24 cycles. Finally, we summarise the implications of these results and suggest future studies that can build upon them.

2. Methodology

2.1. Data

In this study, we use the monthly and 13-month running averaged sunspot numbers from the Sunspot Index and Long-term Solar Observations (SILSO) dataset, including a careful recalibration of the dataset (Clette et al., 2023). Data were downloaded at several points during the analysis phase of this investigation, from 01 January 2022 to 10 October 2022. The additional nine months of data that were subsequently added did not alter the results or conclusions in any material way. We also note that the most recent data remain preliminary. This includes the last five data points in the monthly averaged dataset and the last 12 data points in the 13-month running-averaged dataset.
2.2. Model

We develop a simple, empirical model for predicting the basic macroscopic properties of the solar cycle. It is only applicable once the solar cycle has started. The model posits that once underway, SSN will evolve in a way such that it maintains a constant quantile position with respect to previous cycles. Thus, a basic requirement is that the data already available lie on a path of constant quantile up to the point of the last available data. The model assumes that the constancy of quantile holds when cycles superposed upon one another, with solar-activity minimum being the “zero” in time. This further assumes that the minima can be accurately inferred from the data. For convenience, we call this approach the Quantile-Superposed-Epoch Analysis (Q-SEA) model.

3. Results

Figure 1 shows the monthly sunspot number count (black) and 13-month running average (green), with the minima in each solar-activity cycle marked by the vertical red line, and cycle numbers indicated between them. The data run through September 2022. As noted above, these are taken from the Sunspot Index and Long-term Solar Observations (SILSO) dataset, which includes careful recalibrations of the data. There are several points worth noting, all of which have been well documented in the literature (e.g. Meadows, 1970; Waldmeier, 1971; Shove, 1986; Wilson, 1992; Riley et al., 2022). First, for the last three minima, the depth and duration of the troughs at solar minimum have increased with each minimum, to the point, in fact, that the sunspot number “bottoms out” at the beginning of Cycle 25. Second, longer-term modulations in the amplitudes of the peaks can be inferred, with Cycles 1 – 6, 6 – 13,
Figure 2 The SSN as a function of time for each of the last 25 cycles. The current cycle is presented as a monthly average (thick black curve), whereas the earlier 24 are shown as 13-month running averages for ease in visualization (multiple colours). The “zero” time for each cycle has been aligned with the estimated minimum in solar activity for that cycle. The thick green curve is the average of all 24 cycles. The thick grey curve is Cycle 24.

and 13 – 25 marking three distinct envelopes. Although speculative, these variations suggest that a single small peak is usually followed by several more moderate ones (e.g. Cycles 5, 6, and 7), with little evidence that a very small peak (e.g. Cycle 24) can be followed by a substantially larger one. Third, when cycles are grouped into consecutively paired even–odd cycles, the odd-following cycle is generally larger. Such patterns are not explicitly accounted for in the statistical model developed here. Instead, each cycle, including the new one being predicted, represents a member of a set of “self-similar” cycles.

To explore the variation in size and duration in more detail, in Figure 2 we present a superposed-epoch analysis of the last 25 cycles as a function of time from the point of solar minimum. Cycles 1 – 24 are shown as 13-month averages to aid in their interpretation (we show the monthly averaged data later), while Cycle 25, which is ongoing, is shown as monthly averages (thick black curve). The average of all 24 cycles is shown in green and Cycle 24 is emphasized by the thicker grey line. Several points are worth remarking upon. First, there is a huge range of peak values, from below 100 to almost 300. Second, the peaks occur at various points along the cycle, but there is a tendency for larger cycles to peak sooner than weaker cycles. Third, cycles show considerable variability in duration, as evidenced by the location of the following minimum (right-hand side of the plot), which occurs roughly between years 9 and 12. Fourth, focusing on Cycle 25, we infer that it is increasing along a similar trajectory as Cycle 24. Although the less-averaged points do cross multiple previous cycles, in general there appear to be six curves below it and 18 curves above it. Thus, it lies roughly at the 25th percentile. Finally, we note that the current cycle appears to be substantially less active than the average of all 24 previous cycles (green).

To investigate the quantile position more quantitatively, we interpolated each cycle onto a higher-resolution time-series (varying $\Delta t$ from 0.01 to 0.1 years to verify that the results
Figure 3  The SSN as a function of time for the first four years of each cycle. The current cycle is presented as a monthly average (black curve), whereas the earlier 24 cycles are shown as 13-month running averages (multiple colours) and the average of all 24 cycles is shown by the green curve. The solid blue lines are linear fits to each of the curves for the time interval shown.

were not sensitive to the procedure) using the monthly datasets and ranked Cycle 25 data at each point in time. Although there was initially some variation due to the generally low values, once the cycle began to take off, Cycle 25 consistently placed at rank 6 out of 25. Specifically, for the interval 13–24 months, the modal quantile was found to be overwhelmingly 25% (6/24).

To verify the robustness of this result, we then fit a two-year interval commencing nine months after the beginning of the cycle using either an exponential model or a linear model. The former, unfortunately, did not visually capture a significant fraction of the cycles since the point of exponential rise differed from one cycle to the next. On the other hand, a linear fit seemed to visually perform reasonably well. These results are shown in Figure 3, where four years of each cycle are shown, with the fits to these curves shown by the blue lines. Cycle 25, in terms of gradient, ranked 7th out of 25 (i.e., the 28th percentile).

Based on these estimates of the quantile position of Cycle 25 relative to previous cycles, we then built a model prediction for the entire cycle such that, at each point along the cycle, the SSN would be the 25th percentile of all values at that point in time. That is, at each time, the SSNs from the previous 24 cycles were ordered from smallest to largest, and the value at the first quartile (25th percentile) was chosen for the prediction value. This prediction is shown by the red curve in Figure 4. In this case, we used the monthly averages for all cycles to make the prediction. Also emphasized in the plot is the variation for Cycle 24 (thick grey line), which can be seen to track the predicted trajectory for Cycle 25, with a peak value of \(\approx 120\). The average cycle (using the previous 24 cycles) is shown by the thick green line. Of particular note is that the observed values for Cycle 25 (thick black curve), which were not used in the prediction, overlay the prediction for Cycle 25 remarkably well. Additionally, both the observed and predicted values for Cycle 25 lie significantly below the average cycle values.
Figure 4  The SSN as a function of time for each of the last 25 cycles. In contrast to Figure 2, monthly (not 13-month running averages) are shown for each previous cycle. The thick black line again shows observed SSN from Cycle 25, while the thick red line shows the predicted Q-SEA values. For comparison, Cycle 24 is highlighted by the thicker grey line, and the average cycle is shown in green.

We repeated the analysis using the 13-month running average of the previous cycles. This is shown in Figure 5. Again, the predicted cycle is relatively weak and tracks the evolution of Cycle 24 reasonably well. In this case, comparison between the monthly values for Cycle 25 (black curve) and the predicted 13-month running averages (red curve) do not lie on top of each other as well as in Figure 4; however, this is likely a statistical artefact of comparing monthly and 13-monthly averages.

While suggestive, the results so far merely imply a promising technique. To better assess and validate the model, we repeated the analysis for each of the previous 24 cycles, assuming that only the first two years of the cycle had elapsed. To estimate the quantile for each cycle, we took the modal quantile value for months 13–24. In all cases, there was a clear modal value that could be used to build up a forecast for that cycle. Figure 6 compares the observed SSN profile (solid line) with the predicted profile (dashed line), where each color denotes a particular cycle. The region between the observed and predicted SSNs is colored semi-transparently. So, for example, the very weak Cycle 6 (pink) can be seen to deviate from the observations during years two to four of the cycle but match very well for years five through ten. This makes intuitive sense since the database of observed cycles does not contain any cycles that are (at least initially) weaker than this. As a second example, the double-peaked Cycle 23 (yellow) prediction matches extremely well through the first peak, showing some disagreement in the early declining phase, before once again matching the observed values. Finally, and unsurprisingly, perhaps, the largest cycle of the interval (19, green) shows the largest mismatch between the observations and the predictions since there are no comparable cycles in the observed dataset from which to base a forecast. In general, at least in a qualitative sense, there appears to be a good match between predictions and observations.
Figure 5  The SSN as a function of time for each of the last 25 cycles. In contrast to Figure 4, 13-month running averages are shown for each previous cycle. The thick black line again shows observed monthly SSN from Cycle 25, while the thick red line shows the predicted Q-SEA values based on the 13-month data. The thick grey curve is Cycle 24.

To quantify this, we than computed the mean absolute error (MAE) between the forecasted SSN profile and the SSN profile that was observed. We also computed the MAE for the “baseline” (or “reference”) model, which we choose to be the average-cycle profile (the green curves in previous figures). The degree to which the former errors are less than the latter provides support for the Q-SEA model. In Figure 7, we show the ratio of MAE(Q-SEA) to MAE(average). A distribution centred on 1.0 would suggest that the Q-SEA model was no better than the baseline model; however, a distribution shifted to the left, would favour Q-SEA. We found that 75% (18 out of 25) of the cycles were better predicted using the Q-SEA approach. We note also that the area under the curve is not representative of the relative merits of the two models since a ratio is being displayed (thus, for example, a value of 2.0 for MAE(average) would be equivalent to a value of 0.5 for MAE (Q-SEA)).

4. Summary and Discussion

In this study, we developed a novel superposed-epoch analysis that can be updated on a monthly basis, and which currently predicts that Solar Cycle 25 will be a very modest cycle (within the 25th percentile of all numbered cycles), with a monthly averaged (13-month average) peak of $\approx 130 (110)$, likely occurring in December 2024. These results are generally consistent with most predictions that suggest Cycle 25 will be a weak cycle but contradict several prominent and more extreme predictions arguing that the current cycle will rival the strongest cycles in recorded history.

The simple model explored here has several potentially limiting assumptions. The first is whether it is reasonable to assume that once underway, a cycle will maintain its relative
Figure 6  Comparison of 13-month averaged SSN with predicted profile using the Q-SEA method. Data are shown by the solid lines, while dashed lines represent the forecasts. The region between the model and observations is semi-transparently coloured to emphasise the error in the prediction.

Figure 7  Density distribution of the ratio of MAE(QSEA) versus MAE(average), where the latter refers to a prediction based on the average value of the SSN for all 24 cycles.

order with respect to other cycles. The dynamo is intrinsically stochastic in nature, and, thus, it is not unreasonable to believe that random fluctuations below the surface could result in significant, long-term and large-scale changes to the pattern of active regions. However, a comparison of the Q-SEA model with a baseline profile derived from the “average cycle” further supports the value of the approach, with it outperforming the latter 75% of the time. This suggests that while deviations can occur, a cycle seems to maintain its quantile position reasonably well. A second assumption is that we can accurately identify the “true” minimum in the cycle and, further, that this is a reliable marker for the onset of the next cycle. It is conceivable that a different metric of this would lead to different conclusions. However, the close alignment of the observed data for Cycle 25 and the predicted values during the entire
2.5 years since the minimum of December 2019 suggests that this is a reasonable assumption to make. A third assumption is that the cycles are “self-similar”, in the sense that they can be superposed on one another such that their trajectories are reasonably well aligned. However, even a cursory glance at Figures 6 demonstrates that this assumption is violated. Of course, this criticism can be leveled at most, if not all, models aimed at forecasting the evolution of an entire cycle. The key issue is whether there is value in the current prediction. Here, we have only demonstrated that the model outperforms a reference model based on the “average” cycle over the previous 24 cycles. A future study aims to compare the Q-SEA model with a variety of statistical models to assess to what extent it under- or out-performs them.

Our approach can be contrasted with a number of other forecast approaches, particularly those that can be applied once the cycle has begun. The following schemes are illustrative of those that have been developed rather than exhaustive. In one of the earliest models, McNish and Lincoln (1949) used the concept of a “mean cycle”, with a correction dependent on the difference of the earlier values of the cycle from the mean cycle, to predict SSN up to one year ahead. Hanslmeier, Denkmayr, and Weiss (1999) used a non-parametric regression technique (the “combined method”) for long-term prediction of sunspot numbers by using a weighted average of past cycles of similar size. These, together with Waldmeier’s “standard method”, a least-square fit and interpolation of a set of standard curves, are used by the World Data Center (WDC) Sunspot Index and Long-term Solar Observations (SILSO) team to make real-time predictions of the SSN from one to 12 months ahead. Additionally, Hathaway, Wilson, and Reichmann (1994) proposed a simple, functional form for SSN, being described by four parameters: starting time, amplitude, rise time, and asymmetry. Moreover, the asymmetry parameter varied little from one cycle to the next, and rise time was found to correlate well with amplitude, further reducing the number of required parameters to two. More recently, Cameron and Schüssler (2008) predicted the amplitude of the following maximum using the average growth rate of the SSN. Similarly, Podladchikova et al. (2022) used the maximal growth rate of the SSN in the ascending phase of the cycle to predict the subsequent amplitude. An obvious question, but one that is beyond the scope of the present study, is to ask how well each of these approaches performs against one another. In the past, such comparisons have been made by independent researchers (e.g. Pesnell, 2020), or collaborations amongst the various forecast teams. In a follow-on to this study, we are planning to pursue the latter possibility.

Our primary purpose in this study was to present the Q-SEA technique. We also presented a retrospective forecast, suggesting that it performs better than a baseline model. Pragmatically, however, as Hathaway (2015) has suggested, it is likely that the Q-SEA model will fair only as well as previous statistical approaches have, being limited – in one form or another – to extrapolation of patterns that are already present in the historical dataset. Instead, to overcome these intrinsic limitations, it is likely that mechanistic models are required, ones that incorporate the non-linearity of the system, as well as being driven by the widest array of available data, such as observations of the photospheric magnetic field.

Our analysis, interpretation, and conclusions differ substantially from those of McIntosh et al. (2020), who suggested that “sunspot Solar Cycle 25 could have a magnitude that rivals the top few since records began”. Instead, our results support a growing chorus of studies that appear to rule out this possibility (e.g. Ahluwalia, 2022; Carrasco and Vaquero, 2022). Interestingly, even now, the McIntosh et al. interpretation is highlighted disproportionately in both scientific presentations, news publications, and social media (e.g. Phillips, 2022; Pultarova, 2022). Its current popularity, while a natural consequence of extreme predictions being more “newsworthy”, also benefits from a fortuitous alignment of a short section of
the current rise portion of the cycle with their prediction. Figure 1 from Phillips (2022), for example, suggests that, indeed, the McIntosh et al. (2020) forecast appears to match a limited portion of the rise phase very well. However, a crucial oversight is a mismatch from solar minimum (December 2019) until mid-2021, where their prediction underestimated the observed values.

In closing, we reiterate that our primary goal was to present a simple technique for predicting the evolution of the solar cycle by placing the current cycle at a particular quantile, and extrapolating from that using the available previous cycles. This approach is, in many ways, complementary to other empirical-based approaches that are applicable only after the cycle has begun. Our aim has not been to demonstrate that this approach is necessarily better than any of these approaches. This will be the topic of a future investigation. Instead, we present it as a logical extrapolation procedure, which is consistent with many of the predictions that have been previously made, including the consensus prediction (subject to a shift in timing) produced by NOAA. It is also presented as a counter to more extreme predictions suggesting that the current cycle is going to rival the largest cycles of the space era. Our results suggest that this, while possible, is extremely unlikely.

Author contributions P. Riley conceived of the study, performed all analyses, and wrote and reviewed the manuscript.

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Data Availability All data analysed in this study can be downloaded from www.sidc.be/silso/datafiles. However, for convenience, and to the extent that these data may change, we are also making the data available with the source code at the following GitHub repository: github.com/predsci/QSEA-ssn-prediction.

Code Availability All code necessary to reproduce the figures and analysis presented here is being made available through the following GitHub repository: github.com/predsci/QSEA-ssn-prediction.

Declarations

Competing interests The authors declare no competing interests.

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