Predicting the solar maximum with the rising rate

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ABSTRACT

The growth rate of solar activity in the early phase of a solar cycle has been known to be well correlated with the subsequent amplitude (solar maximum). It provides very useful information for a new solar cycle as its variation reflects the temporal evolution of the dynamic process of solar magnetic activities from the initial phase to the peak phase of the cycle. The correlation coefficient between the solar maximum ($R_{\text{max}}$) and the rising rate ($\beta_a$) at $\Delta m$ months after the solar minimum ($R_{\text{min}}$) is studied and shown to increase as the cycle progresses with an inflection point ($r = 0.83$) at about $\Delta m = 20$ months. The prediction error of $R_{\text{max}}$ based on $\beta_a$ is found within estimation at the 90% level of confidence and the relative prediction error will be less than 20% when $\Delta m \geq 20$. From the above relationship, the current cycle (24) is preliminarily predicted to peak around October, 2013 with a size of $R_{\text{max}} = 84 \pm 33$ at the 90% level of confidence.

Subject headings: solar physics; solar activity; sun spots; solar cycles

1. Introduction

The Waldmeier effect that stronger cycles tend to rise faster is a well known fact in solar activity [Waldmeier 1939; Hathaway et al. 2002; Du et al. 2009]. The growth rate of solar activity ($R_z$) in the early phase of a solar cycle, defined as the ratio of a given increment ($\Delta R_z = 20$) between two certain levels ($R_{z1} = 30$ and $R_{z2} = 50$) over the corresponding elapsed time ($\Delta t$), was found to be highly correlated ($r > 0.8$) with the subsequent amplitude [Cameron & Schüssler 2008]. Therefore, the strength of a new cycle should be rationally predicted by the above relation. The problem is that if and at what month after the start of a new cycle the strength of the cycle can be well estimated from the early information of the cycle.

This paper studies the variation of the correlation between the maximum amplitude ($R_{\text{max}}$) of a solar cycle and the rising rate ($\beta_a$) as a function of $\Delta m$ months entering the cycle and analyzes the predictive power of $\beta_a$ on $R_{\text{max}}$ as the cycle progresses is analyzed in Section 2.1, showing that $r$ is very low near the initial phase ($r < 0.5$ if $\Delta m \leq 10$) and significant only at a few months after the start of the cycle ($r > 0.8$ if $\Delta m \geq 19$). The predictive power of $\beta_a$ on $R_{\text{max}}$ as the cycle progresses is analyzed in Section 2.2, indicating that the relative prediction error of $R_{\text{max}}$ is very small for almost all $\Delta m$ in some cycles and smaller than 20% at some (about twenty) months after the start in other cycles. The peak size and its timing of cycle 24 are estimated in Section 3, followed by conclusions in Section 4.

2. Data and Analysis

The data used in the present study are the smoothed monthly mean international sunspot number ($R_z$) from July, 1749 to February, 2011. The rising rate is defined as the ratio, $\beta_a = (R_z(\Delta m) - R_{\text{min}})/\Delta m$, of the increment of $R_z$ from the minimum ($R_{\text{min}}$) over the elapsed time ($\Delta m$ months). The temporal variation in the correlation coefficient ($r$) between $R_{\text{max}}$ and $\beta_a$ is analyzed in Section 2.1, showing that $r$ is very low near the initial phase ($r < 0.5$ if $\Delta m \leq 10$) and significant only at a few months after the start of the cycle ($r > 0.8$ if $\Delta m \geq 19$). The predictive power of $\beta_a$ on $R_{\text{max}}$ as the cycle progresses is analyzed in Section 2.2, indicating that the relative prediction error of $R_{\text{max}}$ is very small for almost all $\Delta m$ in some cycles and smaller than 20% at some (about twenty) months after the start in other cycles. The peak size and its timing of cycle 24 are estimated in Section 3, followed by conclusions in Section 4.

http://www.ngdc.noaa.gov/stp/spaceweather.html
from the minimum \( R_{\text{min}} \) over the elapsed time \( \Delta m \) from the start of the cycle. The rising rate is computed for each cycle \( n \) and each \( \Delta m \), denoted by \( \beta_n(\Delta m, n) \). The parameters are listed in Table 1 in which \( R_{\text{min}} \) and \( R_{\text{max}} \) are the minimum and maximum amplitudes of the solar cycle, respectively; \( T_n \) is the rise time from minimum to maximum; \( \beta_n(27, n) \) is the value of \( \beta_n(\Delta m, n) \) at the current state \( \Delta m = 27 \); other parameters will be described later; and the last row indicates the relevant averages over cycles \( n = 7–23 \).

2.1. The variation in the correlation between \( R_{\text{max}} \) and \( \beta_n \) as the cycle progresses

Figure 1 illustrates the variation in the correlation coefficient \( r \) between \( R_{\text{max}}(n) \) and \( \beta_n(\Delta m, n) \) for the cycles in which \( T_n(n) \geq \Delta m \) at a given \( \Delta m \) (using only the data in the rising phases). One can see that \( r \) varies with the progression of the cycle \( \Delta m \). A steady increasing trend is shown in \( r \) since \( \Delta m = 6 \): \( r \) increases from about 0.33 at \( \Delta m = 6 \) to about 0.83 at \( \Delta m = 20 \).

\[
\Delta m = 20 \text{ at a high speed, and increases at a smaller speed since then, showing an inflection point at } \Delta m = 20 \text{ months, } r(20) = 0.83. \text{ Near the initial phase } (\Delta m \leq 10) \text{ the correlation is not strong } (r < 0.5). \text{ The correlation coefficient between } R_{\text{max}} \text{ and } \beta_n \text{ is high enough at } \Delta m = 19 \text{ } (r > 0.81) \text{ months entering the solar cycle. At the current state } (\Delta m = 27), r(27) = 0.88.
\]

2.2. The predictive power of \( \beta_n \) on \( R_{\text{max}} \)

In order to test the predictive power of \( \beta_n \) on \( R_{\text{max}} \) at different \( \Delta m \), we use only the data up to cycle \( (n - 1) \) to predict \( R_{\text{max}} \) for cycle \( n \). For a given \( \Delta m \), we calculate the linear regression equation of \( R_{\text{max}}(i) \) against \( \beta_j(\Delta m, i) \) for cycles \( i = 1, 2, \cdots, n - 1 \) in the form of

\[
R_{\text{max}} = A + B\beta_n,
\]

and the standard deviation \( \sigma(\Delta m, n - 1) \) used to estimate the uncertainty of the prediction of \( R_{\text{max}}(n) \). Then, substituting the value of \( \beta_j(\Delta m, n) \) into this equation, the \( R_{\text{max}} \) value for cycle \( n \) can be predicted, which is denoted by \( R_p(\Delta m, n) \). Figure 2 shows the results for the recent nine cycles \( n = 15–23 \): \( R_p(\Delta m, n) \) (black solid line) together with error bars \( t_p(n - 1)\sigma(\Delta m, n - 1) \); \( R_{\text{max}}(n) \) (black horizontal long-dashed line), the actual relative prediction error (red dotted).

\[
E(\Delta m, n) = \frac{|R_p(\Delta m, n) - R_{\text{max}}(n)|}{R_{\text{max}}(n)},
\]

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Table 1: Parameters and results

| \( n \) | \( R_{\text{min}} \) | \( R_{\text{max}} \) | \( T_n \) | \( \beta(27, n) \) | \( E(E_c) \) | \( cc(\text{cc}) \) |
|---|---|---|---|---|---|---|
| 1 | 8.4 | 86.5 | 76 | 0.74 |
| 2 | 11.2 | 115.8 | 40 | 2.23 |
| 3 | 7.2 | 158.5 | 35 | 3.94 |
| 4 | 9.5 | 141.2 | 41 | 3.64 |
| 5 | 3.2 | 49.2 | 82 | 0.45 |
| 6 | 0.0 | 48.7 | 70 | 0.20 |
| 7 | 0.1 | 71.5 | 79 | 0.63 | 0.18(0.80) | -0.15(-0.98) |
| 8 | 7.3 | 146.9 | 40 | 3.58 | 0.15(0.27) | -0.90(-0.98) |
| 9 | 10.6 | 131.9 | 55 | 1.24 | 0.32(0.31) | +0.39(-0.88) |
| 10 | 3.2 | 98.0 | 50 | 1.54 | 0.13(0.47) | +0.11(-0.98) |
| 11 | 5.2 | 140.3 | 41 | 2.49 | 0.09(0.32) | -0.32(-0.98) |
| 12 | 2.2 | 74.6 | 60 | 1.76 | 0.39(0.57) | -0.35(-0.98) |
| 13 | 5.0 | 87.9 | 47 | 2.34 | 0.30(0.49) | +0.18(-0.98) |
| 14 | 2.7 | 64.2 | 49 | 1.42 | 0.43(0.67) | -0.65(-0.96) |
| 15 | 1.5 | 105.4 | 49 | 1.94 | 0.09(0.41) | -0.01(-0.93) |
| 16 | 5.6 | 78.1 | 57 | 1.93 | 0.22(0.52) | -0.30(-0.95) |
| 17 | 3.5 | 119.2 | 43 | 1.99 | 0.15(0.35) | -0.29(-0.96) |
| 18 | 7.7 | 151.8 | 39 | 2.73 | 0.21(0.28) | -0.81(-0.98) |
| 19 | 3.4 | 201.3 | 47 | 5.26 | 0.19(0.20) | -0.96(-0.95) |
| 20 | 9.6 | 110.6 | 49 | 2.42 | 0.06(0.38) | -0.22(-0.97) |
| 21 | 12.2 | 164.5 | 44 | 3.14 | 0.25(0.26) | -0.93(-0.98) |
| 22 | 12.3 | 158.5 | 34 | 4.64 | 0.10(0.31) | +0.65(-0.98) |
| 23 | 8.0 | 120.8 | 47 | 2.21 | 0.09(0.35) | -0.82(-0.98) |
| av. | 5.9 | 119.1 | 49 | 2.43 | 0.20(0.41) | -0.31(-0.96) |
the estimated relative prediction error (green dashed),

$$E_t(\Delta m, n) = \frac{t_r(n - 1)\sigma(\Delta m, n - 1)}{R_{\max}(n)}, \quad (3)$$

where \(t_r(n - 1)\) is the \(t\)-value at the 90% level of confidence in a student's \(t\)-distribution for \(n_t = (n - 3)\) degrees of freedom; and the correlation coefficient between \(R_{\max}(i)\) and \(\beta_a(\Delta m, i)\) (\(r\), blue dash-dotted line, multiplied by 100 to be indicated by the right hand scale). The numbers in the figure (cc) denote the correlation coefficients between \(E_t\) (\(E_t\)) and \(r\).

Figure 2(a) illustrates the results for cycle 15. It is seen that \(R_{\max}\) (black horizontal long-dashed line) is all within the error bars of \(R_p\) at the 90% level of confidence (vertical lines), \(E < E_t\), and \(E < 20\%\) (red horizontal long-dashed line) when \(\Delta m \geq 3\), although there are some fluctuations in both \(E\) and \(E_t\). The anti-correlation coefficient between \(E_t\) and \(r\) is very strong, \(cc_t = -0.93\), implying that the higher the correlation coefficient \((r)\) between \(R_{\max}\) and \(\beta_a\), the smaller the estimated relative prediction error \((E_t)\) from the extrapolation of the relationship between \(R_{\max}\) and \(\beta_a\). However, this is only an estimate in theory rather than in practice. In fact, the correlation coefficient between \(E\) and \(r\) is almost zero, \(cc = -0.01\), implying that the actual relative prediction error is almost uncorrelated to \(r\). That is to say it is uncertain whether a more (less) accurate prediction corresponds to a higher (lower) correlation.

In Figure 2(d) for cycle 18, we test only the results for the rising phase \(\Delta m \leq T_{\theta}(= 39)\). One can see that both \(E\) and \(E_t\) decrease as \(\Delta m\) increases. The anti-correlation coefficient between \(E_t\) and \(r\) is also very strong, \(cc_t = -0.98\). The correlation coefficient between \(E\) and \(r\) is highly negative, \(cc = -0.81\), implying that a more (less) accurate prediction can be obtained from a higher (lower) correlation in this case. In cycle 18, \(R_{\max}\) is always within the error bars of \(R_p\) at the 90% level of confidence, \(E < E_t\). In addition, \(E < 20\%\) when \(\Delta m \geq 26\).

Figure 2(g) shows the results for cycle 21: \(\Delta m \leq T_{\theta}(= 44)\). The results are similar to those in Fig. 2(d): both \(E\) and \(E_t\) decrease as \(\Delta m\) increases; the anti-correlation coefficient between \(E\) (\(E_t\)) and \(r\) is very strong, \(cc = -0.93\) \((cc_t = -0.98)\). At a small \(\Delta m\), \(E\) is large: \(E > E_t\) if \(\Delta m \leq 17\). As the cycle progresses, \(E\) becomes smaller: \(E < E_t\) when \(\Delta m \geq 18\); \(E < 20\%\) when \(\Delta m \geq 26\).

The results in other cycles are similar to those above. The main conclusions in Fig. 2 may be summarized as follows.

1. \(R_{\max}\) (black horizontal long-dashed) is usually within the error bars of \(R_p\) (black solid) at the 90% level of confidence (vertical lines), apart from cycles 19 and 21 when \(\Delta m \leq 16\) and \(\Delta m \leq 17\), respectively;

2. the estimated relative prediction error \(E_t\) (green dashed) tends to decrease as \(\Delta m\) increases; \(E_t\) is highly anti-correlated with the correlation coefficient \(r\) (blue dash-dotted), \(cc_t \approx -0.96\);

3. the actual relative prediction error \(E\) (red dotted) varies with some fluctuations and tends to decrease as \(\Delta m\) increases in some cycles (for \(n = 16 - 19, 21, 23\));

4. there is no established relationship between \(E\) and \(r\), such as \(|cc| > 0.8\) in cycles \(n = 18, 19, 21\) and 23, while \(|cc| \leq 0.3\) in cycles \(n = 15, 16, 17\) and 20, and \(cc\) is even positive in cycle 22 (0.65);

5. \(E < E_t\) for all \(\Delta m\) in cycles \(n = 15 - 18, 20, 22\) and 23; \(E < E_t\) for \(\Delta m \geq 17\) in cycle 19, and for \(\Delta m \geq 18\) in cycle 21;

6. \(E < 20\%\) (red horizontal long-dashed) since a very few months entering the cycle \(\Delta m > 3\) in cycles 15, 20 and 22; \(E < 20\%\) for \(\Delta m \geq 34\) in cycle 16, for \(\Delta m \geq 21\) in cycle 17, for \(\Delta m \geq 26\) in cycle 18, for \(\Delta m \geq 17\) in cycle 19, for \(\Delta m \geq 26\) in cycle 21; and for \(\Delta m \geq 10\) in cycle 23.

In summary, \(\beta_a\) behaved very well in predicting the subsequent \(R_{\max}\): (i) the actual prediction error (known only when the cycle is over) is usually within estimation since about twenty months entering the cycle, \(|R_p(\Delta m, n) - R_{\max}(n)| < t_r(n - 1)\sigma(\Delta m, n - 1)\); (ii) the relative prediction error is usually less than 20% since about twenty months into the cycle; and (iii) \(E\) tends to decrease as the cycle progresses. In some cycles \((n = 15, 20\) and 22, see Figures 2(a), (f) and (h)), the relative prediction error is very small \((E < 10\%)\) at
Fig. 2.— Predictions ($R_p$, black solid line, left hand scale) of $R_{\text{max}}$ (black horizontal long-dashed line) together with error bars ($t_r(n-1)\sigma(\Delta m, n-1)$, vertical line) for cycles 15–23 (panels (a)–(i), respectively), the actual relative prediction error ($E$, red dotted, right hand scale), the estimated value ($E_t$, green dashed), and the correlation coefficient between $R_{\text{max}}$ and $\beta_a$ ($r$, blue dash-dotted). The numbers in the figure (cc) denote the correlation coefficients between $E$ ($E_t$) and $r$.

a small $\Delta m$ even if the correlation coefficient is low ($r < 0.5$). Similar conclusions can also be obtained in other cycles (not shown): $E < E_t$ at about $\Delta m \geq 20$; $E_t$ is highly anti-correlated with $r$ ($cc_t$); while there is no established relationship between $E$ and $r$ ($cc$). The results of $E$ ($E_t$) and $cc$ ($cc_t$) in cycles 7–23 are shown in Table 1 and the relevant averages are indicated by the last row: $< E > = 0.20$ ($< E_t > = 0.41$) and $< cc > = -0.31$ ($< cc_t > = -0.96$), where $E$ is the average over $\Delta m$ in a solar cycle and $< E >$ represents the average over cycles 7–23. Therefore, a higher (lower) correlation coefficient does not necessarily yield a more (less) accurate prediction (Du et al. 2009b; Du & Wang 2011a; Du 2011a).

3. Prediction $R_{\text{max}}$ for Cycle 24

Now, we employ the above technique to predict the peak size of cycle $n = 24$. The results are shown in Fig. 3. $R_p$ (solid) is the predicted $R_{\text{max}}$ and $r$ (dotted) is the correlation coefficient between $R_{\text{max}}(i)$ and $\beta_a(\Delta m, i)$ for cycles $i = 1, 2, \ldots, 23$ at a given $\Delta m$. It is seen that $R_p$ does not vary significantly with $\Delta m$. At the current state ($\Delta m = 27$), the correlation coefficient between $R_{\text{max}}$ and $\beta_a$ is $r(27) = 0.88$, and the regression equation of $R_{\text{max}}$ against $\beta_a$ is

$$R_{\text{max}} = 52.1 + 27.2\beta_a,$$

with a standard deviation of $\sigma = 19.2$. Substituting the current value of $\beta_a(27, 24) = 1.17$ into this equation, the peak sunspot number for
the ongoing cycle (24) is predicted as \( R_p(24) = 84 \pm t_{(23)} \sigma = (84 \pm 33) \) (asterisk), where \( t_{(23)} = 1.721 \) is the t-value at the 90\% level of confidence in a student’s t-distribution for \( n_t = 23 - 2 = 21 \) degrees of freedom.

From the relationship between \( T_a \) and \( R_{\text{max}} \),

\[
T_a = 79.7 - 0.251 \sigma R_{\text{max}}, \quad \sigma = 9.3, \tag{5}
\]

one can estimate the rise time \( T_a \) for cycle 24. Using the predicted value (84) of \( R_{\text{max}}(24) \), one obtains \( T_a(24) = (59 \pm 9) \) months. Therefore, the peak of cycle 24 may probably occur around October, 2013, slightly later than that (May, 2013) by both NASA Marshall Space Flight Center (MSFC)\(^3\) based on a quasi-Planck function and NOAA space prediction center (SWPC)\(^2\) based on a consensus decision of “The Solar Cycle 24 Prediction Panel, and that (June, 2013) based on a modified Gaussian function \cite{Du2011a}.

### 4. Discussions and Conclusions

Studying the correlation between \( R_{\text{max}} \) of a solar cycle and a related parameter is useful to understand the dynamic process of the cycle. A high correlation can be used to estimate the strength of a new solar cycle \cite{Kane2010, Pesnell2008, Messerotti2009, Du2011a, Wang2008, Wang2009, Le2004, Li2009}. For example, Ohl’s geomagnetic precursor method \cite{Ohl1970} succeeded in predicting \( R_{\text{max}} \) in cycles 20–22 \cite{Launder1991, Thompson1993, Shastri1998, Schuessler2007} due to the high correlation coefficients (> 0.8) between \( R_{\text{max}} \) and geomagnetic-based parameters. However, a high correlation does not always yield a satisfactory prediction \cite{Du2009a, Du2011a, Du2011b, Cameron2007, Du2008, Du2010} and a low correlation may also yield an accurate prediction in some cases (see Section 2.2).

A prominent feature in the solar cycle is the so-called Waldmeier effect that stronger cycles tend to rise faster \cite{Waldmeier1939, Hathaway2002, Du2009a, Cameron2008}. This effect has already begun to work in the early phase of the cycle \( (\beta_n) \). The variation in \( \beta_n \) reflects the temporal evolution of the dynamic process of solar magnetic activities from the initial phase to the peak phase of the cycle, and so, \( \beta_n \) can provide very useful information for the cycle.

In this study, we analyzed the temporal variation in the correlation coefficient \( (r) \) between \( R_{\text{max}} \) and \( \beta_n \) as a function of \( \Delta m \) months after the solar minimum \( (R_{\text{min}}) \) and the predictive power of \( \beta_n \) on \( R_{\text{max}} \) as the solar cycle progresses. First, it is shown that \( r \) increases as \( \Delta m \) increases with an inflection point over 0.8 at about \( \Delta m = 20 \) months. The dynamic process of the solar activity is more non-linear near the initial phase of the cycle \( (r < 0.5 \text{ if } \Delta m \leq 10) \) and tends to be stable after twenty months entering the cycle.

Besides, \( \beta_n \) behaved rather well in predicting \( R_{\text{max}} \): the prediction error is usually within the estimated one after about \( \Delta m = 20 \) months entering a solar cycle, \( |R_p(\Delta m, n) - R_{\text{max}}(n)| < t_{(n - 1)}\sigma(\Delta m, n - 1) \) at the 90\% level of confidence. This is a crucial point in prediction because a method will be less useful if the prediction is not within the prediction range derived from the method. In addition, the relative prediction error \( (E) \) based on \( \beta_n \) is usually less than 20\% when \( \Delta m \geq 20 \) months. Thus, \( \beta_n \) is a good indicator for the subsequent \( R_{\text{max}} \). Finally, \( E \) tends to decrease as the cycle progresses. Therefore, the maximum amplitude of a new cycle \( R_{\text{max}} \) can be well estimated at twenty months after the start.

It should be noted in Fig. 2 that the correlation between \( R_{\text{max}} \) and \( \beta_n \) is not strong near the initial phase of the cycle, while the prediction of \( R_{\text{max}} \) from \( \beta_n \) is rather good in some cycles (15, 20, 22 and 23). Therefore, a high correlation is not the sole condition to obtain a more accurate pre-
Accurately predicting the strength of an upcoming solar cycle is important for both solar physics and solar-terrestrial environment. A reliable prediction of $R_{\text{max}}$ may test models for explaining the solar cycle (Presnell 2008). So far, a large number of results have been published on the prediction of $R_{\text{max}}$ for cycle 24, of which some are based on statistics and some others are related to physics (see Table 2). As the solar activity near the minimum between cycles 23 and 24 lasts so long a time at a low level before rising (as shown in the most spotless days since cycle 16, Li et al. 2011, 2010), cycle 24 is unusual, which is drawing greater attention than ever. Besides, as solar dynamo models have begun to be applied in predicting $R_{\text{max}}$ (Choudhuri et al. 2007, Jiang et al. 2007, Dikpati & Gilman 2006), the predictions of the strength of cycle 24 attract special attention in order to test the predictive skill of solar dynamo models.

Discrepancies are found in the predictions of $R_{\text{max}}$ for cycle 24 by event methods (Table 2). Our prediction (84) is near to those by the polar field (or solar dynamo model), about 30% lower than the peak size of cycle 23. Recently, we find that cycle 24 is most likely similar to cycles 14 and 10 (Du & Wang 2011b). Therefore, even if cycle 24 is not a strong cycle, large eruption events may also occur as in cycle 10 for the largest solar storm of the year 1859 (Carrington Event).

Conclusions are summarized below.

1. The correlation coefficient ($r$) between the maximum amplitude ($R_{\text{max}}$) of a solar cycle and the rising rate ($\beta_a$) at $\Delta m$ months after the solar minimum ($R_{\text{min}}$) increases as $\Delta m$ increases with an inflection point at about 20 months entering the cycle.

2. The prediction error based on the linear relationship between $R_{\text{max}}$ and $\beta_a$ is usually within the estimated one when $\Delta m \geq 20$, $|R_p(\Delta m, n) - R_{\text{max}}(n)| < t_c(n-1)\sigma(\Delta m, n-1)$, where $\sigma(\Delta m, n-1)$ is the standard deviation of the regression equation for the data up to cycle n – 1, and $t_c(n-1)$ is the t-value at the 90% level of confidence in a student's t-distribution.

3. The relative prediction error ($E$) from the above technique tends to decrease as the cycle progresses and will be less than 20% when $\Delta m \geq 20$.

4. The current cycle (24) is temporarily predicted to peak around October 2013 with a size of $R_{\text{max}} = 84 \pm 33$ at the 90% level of confidence.

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