

1 **WAVELET ANALYSIS OF THE SINGULAR SPECTRAL RECONSTRUCTED TIME SERIES TO STUDY**
2 **THE IMPRINTS OF SOLAR-ENSO-GEOMAGNETIC ACTIVITY ON INDIAN CLIMATE**

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14 **ABSTRACT**

15 To study the imprints of Solar-ENSO-Geomagnetic activity on the Indian Subcontinent, we have
16 applied the Singular spectral analysis (SSA) and wavelet analysis to the tree ring temperature
17 variability record from the Western Himalayas. The other data used in the present study are the
18 Solar Sunspot Number (SSN), Geomagnetic Indices (aa Index) and Southern Oscillation Index
19 (SOI) for the common time span of 1876-2000. Both SSA and wavelet spectral analyses reveal
20 the presence of 5-7 years short term ENSO variations to 11 year solar cycle indicating the
21 possible combined influences of solar-geomagnetic activities and ENSO on the Indian
22 temperature. Another prominent signal corresponding to 33-year periodicity in tree ring record
23 suggests the Sun-temperature variability link probably induced by changes in the basic state of
24 the earth's atmosphere. In order to complement the above findings we performed wavelet
25 analysis of SSA reconstructed time series, which agrees well with our earlier results and also
26 increases the signals to noise ratio thereby showing strong influence of solar-geomagnetic &
27 ENSO throughout the entire time period. The solar flares are considered to be responsible for
28 causing the atmosphere circulation patterns. The net effect of solar-geomagnetic processes on
29 temperature record might suggest counteracting influences on shorter (about 5–6 y) and longer
30 (about 11–12 y) time scales. The present analyses suggest that the influence of solar activities
31 on Indian temperature variability operates in part indirectly through coupling of ENSO on
32 multilateral time scales. The analyses, hence, provide credible evidence for tele-connections of
33 tropical pacific climatic variability and Indian climate ranging from inter-annual-decadal time

34 scales and also suggest possible role of exogenic triggering in reorganizing the global earth-
35 ocean-atmospheric systems.

36 **Key words:** *Geomagnetic activity, Western Himalayas, Sunspot Number, SOI index, Singular*
37 *spectral analysis, Wavelet spectrum, Coherency.*

38

39 **1. Introduction:**

40 Several recent studies of solar/geomagnetic effects on climate have been examined on both
41 global as well as on regional scales (Lean and Rind, 2008; Benestaed and Schmidt, 2009; Meehl,
42 2009; Kiladis and Diaz 1989; Pant and Rupa Kumar 1997; Gray et al. 1992; Wiles et al. 1998; Friis
43 and Svensmark 1997; Rigozo et al. 2005; Feng et al. 2003; Tiwari and srilakshmi 2009; Chowdary
44 et al. 2006, 2014; Appenzeller et al. 1998; Proctor et al. 2002; Tsonis et al. 2005; Freitas and
45 Mclean 2013). The Sun's long-term magnetic variability caused by the sunspots is considered as
46 one of the primary drivers of climatic changes. The short-term magnetic variability is due to the
47 disturbances in Earth's magnetic fields caused by the solar activities and is indicated by the
48 geomagnetic indices. The Sun's magnetic variability modulates the magnetic and particulate
49 fluxes in the heliosphere. This determines the interplanetary conditions and imposes significant
50 electromagnetic forces and affects upon the planetary atmosphere. All these effects are due to
51 the changing solar-magnetic fields, which are relevant for planetary climates including the
52 climate of the Earth. The Sun-Earth relationship varies on different time scales ranging from
53 days to years bringing a drastic influence on the climatic patterns. The ultimate cause of solar
54 variability, at time scales from decadal to centennial to millennial or even longer scales has its
55 origin in the solar dynamo mechanism. During the solar maxima, huge amounts of solar energy
56 particles are released, thereby causing the geomagnetic disturbances. The 11 years solar cycle
57 acts as an important driving force for variations in the space weather, ultimately giving rise to
58 climatic changes. It is, therefore, imperative to understand the origin of space climate by
59 analyzing the different proxies of solar magnetic variabilities. Another most important
60 phenomena is El Nino-Southern Oscillation (ENSO), which produces droughts, floods and
61 intense rainfall. The strong coupling and interactions between the Tropical Ocean and
62 atmosphere play a major role in the development of global climatic system. The El Nino events

63 generally recur approximately every 3-5 years with large events spaced around 3-7 years apart.
64 The ENSO phenomena have shown huge impact on the Asian monsoon (Cole et. al., 1993),
65 Indian monsoon (Chowdary et al. 2006, 2014) as well as globally (Horel and Wallace 1981;
66 Barnett 1989; Yasunari 1985; Nicholson 1997). In particular, the El Nino, solar, geomagnetic
67 activities are the major affecting forces on the decadal and interdecadal temperature variability
68 on global and regional scales in a direct/indirect way (Gray et al., 2010). Recent studies
69 (Frohlich and Lean 2004; Steinhilber et al. 2009) indicate the possible influence of solar activity
70 on Earth's temperature/climate on multi-decadal time scales. The 11 year solar cyclic variations
71 observed from the several temperature climate records also suggest the impact of solar
72 irradiance variability on terrestrial temperature (Budyko 1969; Friis and Lassen 1991; Friis and
73 Svensmark 1997; Kasatkina et al. 2007). The bi-decadal (22 years) called the Hale cycle, is
74 related to the reversal of the solar magnetic field direction (Lean et al. 1995; Kasatkina et al.
75 2007). The 33 year cycle (Bruckener cycle) is also caused by the solar origin, but it is a very rare
76 cycle (Kasatkina et al. 2007). The 2–7 years ENSO cyclic pattern and its possible coupling
77 process is the major driving force for the temperature variability (Gray et al. 1992; Wiles et al.
78 1998; Mokhov et al. 2000; Rigozo et al. 2007, Kothawale et al. 2010). El-Borie et al, 2010 have
79 indicated the possible contributions for both the solar and geomagnetic indices. El-Borie and
80 Al-Thoyaib, 2006 and El-Borie et al., 2007 have indicated in their studies that the global
81 temperature should lag the geomagnetic activity with a maximum correlation when the
82 temperature lags by 6 years. Mendoza et. al., 1991 reported on possible connections between
83 solar activity and El Nino's, while Reid and Gage (1988) and Reid (1991) reported on the
84 similarities between the 11-year running means of monthly sunspot numbers and global sea
85 surface temperature. These findings suggest that there is possibility of strong coupling between
86 temperature-ENSO and solar-geomagnetic signals.

87 The mean global temperature of the Earth's surface also plays a very important role in
88 bringing climatic changes. Several studies have been carried out to understand the detailed
89 climatic changes of India in the past millennium using various proxy records e.g. ice cores, lake
90 sediments, glacier fluctuations, peat deposits etc. The availability of high-precision and high-
91 resolution palaeo-climatic information for longer time scale from the Indian subcontinent is

92 very less. In recent years, tree-ring data is promising proxy to retrieve high resolution past
93 climatic changes from several geographical regions of India (Bhattacharyya et al. 1988;
94 Bhattacharyya et al. 1992; Hughes, 1992; Bhattacharyya and Yadav, 1996; Borgaonkar et al.
95 1996; Chaudhary et al. 1999; Yadav et al. 1999; Bhattacharyya and Chaudhary, 2003;
96 Bhattacharyya et al. 2006; Shah et al. 200) It has been noted that tree-ring based climatic
97 reconstructions in India generally do not exceed beyond 400 years records except at some sites
98 in the Northwest Himalaya. Thus, a long record of tree-ring data is needed to extend available
99 climate reconstruction further back to determine climatic variability in sub-decadal, decadal
100 and century scale. However, non availability of older living trees in most of the sites is hindering
101 the preparation of long tree chronology. In previous study (Tiwari and Srilakshmi, 2009) have
102 studied the periodicities and non-stationary modes in the tree ring temperature data from the
103 same region (AD 1200-2000). To gain significant connections among the Solar-geomagnetic-
104 ENSO 'triad' phenomena on tree ring width in detail for the time period from 1876-2000, we
105 have applied here the Singular spectral analysis (SSA) and the wavelet spectral analysis for
106 Sunspot data, geomagnetic data (aa index), Troup Southern Oscillation Index (SOI) and the
107 Western Himalayas tree ring data. Our main objective here is to present a wavelet-based
108 analysis of SSA reconstructed time series to focus on the evidence of the ENSO-solar-
109 geomagnetic connections in comparison to ENSO-geomagnetic and solar-ENSO connections.

110

111 **2. Source and Nature of Data:**

112 The data analyzed here includes the time series of (1) Smoothed Sunspot number for solar
113 activity (2) Geomagnetic activity data (aa indices) (3) Troup Southern Oscillation Index (SOI) for
114 the study of El Nino-Southern Oscillation called ENSO (4) Western Himalayan temperature
115 variability record. All the data sets have been analyzed for a common period of 125 years
116 spanning over 1876-2000. The monthly sunspot number data has been obtained from the
117 Sunspot Index Data Center [http:// astro.oma.be/SIDC/](http://astro.oma.be/SIDC/). The Troup SOI data is obtained from the
118 Bureau of Meteorology of Australia, <http://www.bom.gov.au/climate/>. The data for
119 geomagnetic activity, aa Index, was provided by the National Geophysical Data Center, NGDC,
120 (<http://www.ngdc.noaa.gov/stp/GEOMAG/aastar.shtml>). The aa index is a measure of

121 disturbances level of Earth's magnetic field based on magnetometer observations at two, nearly
122 antipodal, stations in Australia and England. In recent studies, the tree ring proxy climate
123 indicators have been potentially used for extracting information regarding past seasonal
124 temperature or precipitation/drought based on the measurements of annual ring width. The
125 detailed description of the data has been presented elsewhere (Yadav et. al., 2004). A brief
126 account of the data pertinent to the present analysis, however, is summarized here. The tree
127 ring data being analyzed here is one of the best temperature variability records (1876 to 2000)
128 of the pre-monsoon season in the Western Himalayas. The mean temperature series is
129 obtained from nine weather stations including both from high and low elevation areas in the
130 Western Himalayas. Temperature variability history is based on widely spread pure Himalayan
131 cedar (*Cedrus deodara* (Roxb.) G. Don) trees and characterizes all the sites with almost no
132 ground vegetation and thereby minimizes individual variation in tree-ring sequences induced by
133 inter tree competition (Yadav et. al., 2004). The mean chorological structure is based on in total
134 60 radii from 45 trees, statistical feature of which show that the chronology is suitable for
135 dendro-climatic studies back to AD 1226 (Yadav et. al., 2004).

136 *(Figure 1)*

137

138 **3. Methods applied:** To analyze the temporal series and to find the climatic structure, we have
139 here applied three methods: Principal component analysis (PCA), Singular Spectral analysis
140 (SSA) and wavelet analysis.

141 **3.1. Principal component analysis (PCA):** As a preliminary analysis, we have applied the
142 Principle component analysis (PCA) to the data sets to extract the principle components. PCA
143 technique is applied for the reduction and extraction for dimensionality of the data and to rate
144 the amount of variation present in the original data set. The purpose to apply the PCA is to
145 identify patterns in the given time series. The new components thereby obtained by the PCA
146 analysis are termed as PC1, PC2, PC3 and so on, (for the first, second and third principal
147 components) are independent and decrease the amount of variance from the original data set.
148 PC1 (the first component) captures most of the variance; PC2 captures the second most of the
149 variance and so on. These components are treated as climatic factors or climatic structures.

150 **3.2. Singular spectral analysis:** The Singular Spectrum Analysis (SSA) method was developed as
 151 the new time series method since 1970s. This method is designed to extract as much
 152 information as possible from a short, noisy time series without any prior knowledge about the
 153 dynamics underlying the series (Broomhead and King, 1986; Vautard and Ghil, 1989). The
 154 method is a form of principal component analysis (PCA) applied to lag-corrections structures of
 155 the time series. The basic SSA decomposes an original time series into a new series which
 156 consists of trend, periodic or quasi-periodic and white noises according to the singular value
 157 decomposition (SVD) and provides the reconstructed components (RCs). The basic steps
 158 involved in SSA are: decomposition (involves embedding, singular value decomposition (SVD))
 159 and reconstruction (involves grouping and diagonal averaging). Embedding decomposes the
 160 original time series into the trajectory matrix; SVD turns the trajectory matrix into the
 161 decomposed trajectory matrices. The reconstruction stage involves grouping to make
 162 subgroups of the decomposed trajectory matrices and diagonal averaging to reconstruct the
 163 new time series from the subgroups.

164 **Step1: Decomposition:**

165 **(a) Embedding:** The first step in the basic SSA algorithm is the embedding step where
 166 the initial time series change into the trajectory matrix. Let the time series be $Y = \{y_1, \dots, y_N\}$
 167 of length N without any missing values. Here the window length L is chosen such that $2 < L <$
 168 $N/2$ to embed the initial time series. We map the time series Y into the L lagged vectors, $Y_i =$
 169 $\{y_i, \dots, y_{i+L-1}\}$ for $i = 1, \dots, K$, where $K = N - L + 1$. The trajectory matrix T_Y ($L \times K$ dimensions) is

170 written as: $T_Y = \begin{pmatrix} Y_1 \\ Y_2 \\ \cdot \\ \cdot \\ Y_K \end{pmatrix} \dots\dots\dots(1)$

171 **(b) Singular Value Decomposition (SVD):** Here we apply SVD to the trajectory matrix T_Y
 172 to decompose and obtain $T_Y = UDV'$ called eigentriples; where U_i ($K \times L$ dimensions; $1 < i < L$) is an
 173 orthonormal matrix; D_i ($1 < i < L$) is a diagonal matrix of order L ; V_i ($L \times L$ dimensions; $1 < i < L$) is
 174 a square orthonormal matrix.

175 The trajectory matrix is thus written as $T_Y = \sum_{i=1}^d U_i \sqrt{\lambda_i} V_i^T$;(2)

176 where the i^{th} Eigen triple of $T_i = U_i \times \sqrt{\lambda_i} \times V_i^T$, $i = 1, 2, 3, \dots, d$ in which $d = \max(i: \sqrt{\lambda_i} > 0)$.

177 **Step 2: Reconstruction:**

178 **(c) Grouping:** Here the matrix T_i is decomposed into subgroups according to the trend,
 179 periodic or quasi-periodic components and white noises. The grouping step of the
 180 reconstruction stage corresponds to the splitting of the elementary matrices T_i into several
 181 groups and summing the matrices within each group. Let $I = \{i_1, i_2, \dots, i_p\}$ be the group of indices
 182 i_1, \dots, i_p . Then the matrix T_I corresponding to the group I is defines as $T_I = T_{i_1} + T_{i_2} + \dots + T_{i_p}$. The split of
 183 the set of indices $J = 1, 2, \dots, d$ into the disjoint subsets I_1, I_2, \dots, I_m corresponds to the equation ()

184
$$T = T_{I_1} + T_{I_2} + \dots + T_{I_m}. \quad \dots\dots\dots(3)$$

185 The sets I_1, \dots, I_m are called the eigen triple grouping.

186 **(d) Diagonal averaging:** The diagonal averaging transfers each matrix T into a time
 187 series, which is an additive component of the intital time series Y . If z_{ij} stands for a element
 188 matrix Z , the k th term of the resulting series is obtained by averaging z_{ij} over all i, j such that
 189 $i+j=k+2$. This is called diagonal averaging or the Hankelization of the matrix Z . The Hankel matrix
 190 HZ , is the trajectory matrix corresponding to the series obtained by the result of diagonal
 191 averaging.

192 Considering equation (3), let X ($L \times K$) matrix with elements x_{ij} , where $1 \leq i \leq L$, $1 \leq j \leq K$.
 193 Here diagonal averaging transforms matrix X to a series g_0, \dots, g_{T-1} using the formula:

194
$$g_k = \begin{cases} \frac{1}{k+1} \sum_{m=1}^{k+1} x_{m, k-m+2}^* & 0 \leq k < L^* - 1 \\ \frac{1}{L^*} \sum_{m=1}^{L^*} x_{m, k-m+2}^* & L^* - 1 \leq k < K^* \\ \frac{1}{T-k} \sum_{m=k-k^*+2}^{N-k+1} x_{m, k-m+2}^* & K^* - 1 \leq k < T \end{cases} \quad (4)$$

195 This diagonal averaging by equation (4) applied to the resultant matrix X_{in} , produces time series
 196 Y_n of length T . For such signal characteristics, it is essential to examine the time-frequency
 197 pattern as to understand whether a particular frequency is temporally consistent or

198 inconsistent. Hence for non-stationary signals, we need a transform that will be useful to obtain
199 the frequency content of the time series/signal as a function of time.

200 An alternative method for studying the non-stationarity of the time series is wavelet
201 transform. For non-stationary signals, wavelets decomposition would be the most appropriate
202 method because the analyzing functions (the wavelets function) are localized both in time and
203 frequency.

204

205 **3.3. Wavelet spectral analysis:** During the past decades, wavelet analysis has become a popular
206 method for the analysis of aperiodic and quasi-periodic data (Grinsted et. al., 2004; Jevrejeva
207 et. al., 2003; Torrence and Compo, 1998; Torrence and Webster, 1999). In particular, it has
208 become an important tool for studying localized variations of power within a time series. By
209 decomposing a time series into time-frequency space, the dominant modes of variability and
210 their variation with respect to time can be identified. The wavelet transform has various
211 applications in geophysics, including tropical convection (Weng and Lau 1994), the El Niño–
212 Southern Oscillation (Gu and Philander 1995), etc. We have applied the wavelet analysis to
213 analyze the non-stationary signals which permits the identification of main periodicities of
214 ENSO-sunspot-geomagnetic in the time series. The results give us more insight information
215 about the evolution of these variables in frequency-time mode.

216 A wavelet transform requires the choice of analyzing function Ψ (called “mother
217 wavelet”) that has the specific property of time-frequency localization. The continuous wavelet
218 transform revolves around decomposing the time series into scaling components for identifying
219 oscillations occurring at fast (time) scale and other at slow scales. Mathematically, the
220 continuous wavelets transform of a time series $f(t)$ can be given as:

221
$$W_{\psi}(f)(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi\left(\frac{t-b}{a}\right) dt \dots\dots\dots(5)$$

222 Here $f(t)$ represents time series, Ψ is the base wavelets function (here we have chosen the
223 Morlet function), with length that is much shorter than the time series $f(t)$. W stands for
224 wavelet coefficients. The variable ‘ a ’ is called the scaling parameter that determines the
225 frequency (or scale) so that varying ‘ a ’ gives rise to wavelet spectrum. The factor ‘ b ’ is related to

226 the shift of the analysis window in time so that varying b represents the sliding method of the
227 wavelet over f(t).

228 In several recent analyses, complex Morlet wavelet has been found useful for
229 geophysical time series analysis. The Morlet is mostly used to find out areas where there is high
230 amplitude at certain frequencies. The complex Morlet wavelet can be represented by a periodic
231 sinusoidal function with a Gaussian envelope and is excellent for Morlet wavelet may be
232 defined mathematically, as follows:

$$233 \quad \psi(t) = \pi^{-1/4} e^{-i\omega_0 t} e^{-t^2/2} \dots\dots\dots(6)$$

234 where ω_0 is a non-dimensional value. ω_0 is chosen to be 5 to make the highest and lowest
235 values of ψ approximately equal to 0.5, thus making the admissibility condition satisfied. The
236 complex valued Morlet transform enables to extract information about the amplitude and
237 phase of the signal to be analyzed. Wavelet transform preserves the self-similarity scaling
238 property, which is the inherent characteristic feature of deterministic chaos. The continuous
239 wavelet transform has edge artifacts because the wavelet is completely localized in time. The
240 cone of influence (COI) is the area in which the wavelet power caused by a discontinuity at the
241 edge has dropped to e^{-2} of the value to the edge. The statistical significance of the wavelet
242 power can be assessed relative to the null hypotheses that the signal is generated by a
243 stationary process with a given background power spectrum (P_k) of first order autoregressive
244 (AR1) process. (Grinsted et. al., 2004)

$$245 \quad P_k = \frac{1 - \alpha^2}{|1 - \alpha e^{-2i\pi k}|^2} \dots\dots\dots(7)$$

246 where k is Fourier frequency index.

247 The cross wavelet transform is applied to two time series to identify the similar patterns
248 which are difficult to assess from a continuous wavelet map. Cross wavelet power reveals areas
249 with high common power. The cross wavelet of two time series x (t) and y (t) is defined as $W^{xy} =$

250 $W^X W^{Y*}$, where * denotes complex conjugate. The cross wavelet power of two time series with
 251 background power spectra P_k^X and P_k^Y is given as

252
$$D\left(\frac{|W_n^X(s)W_n^{Y*}(s)|}{\sigma_X\sigma_Y} < p\right) = \frac{Z_v(p)}{v} \sqrt{P_k^X P_k^Y}, \dots\dots\dots(8)$$

253 where $Z_v(p)$ is the confidence level associated with the probability p for a pdf defined by the
 254 square root of the product of the two χ^2 distributions (Torrence and Compo, 1998). The
 255 wavelet power is $|W_n^X(s)|^2$ and the complex argument of $|W_n^X(s)|$ can be interpreted as the local
 256 phase. The cross wavelet analysis gives the correlation between the two time series as function
 257 of period of the signal and its time evolution with a 95% confidence level contour. The
 258 statistical significance is estimated using red noise model.

259 Wavelet coherence is another important measure to assess how coherent the cross
 260 wavelet spectrum transform is in time frequency space. The wavelet coherence of two time
 261 series is defined as (Torrence and Webster, 1998)

$$R_n^2(s) = \frac{|S(s^{-1} W_n^{XY}(s))|^2}{S(s^{-1} |W_n^X(s)|^2) \cdot S(s^{-1} |W_n^Y(s)|^2)} \dots\dots\dots(9)$$

262 where S is a smoothing operator. The smoothing operator is written as $S(W) = S_{scale}(S_{time}$
 263 $(W_n(s)))$, where S_{scale} denotes smoothing along the wavelet scale axis and S_{time} smoothing in
 264 time. Here for the morelet wavelet, the smoothing operator is

266
$$S_{time}(W)|_s = \left(W_n(s) * c_1 \frac{-t^2}{2s^2} \right) \dots\dots\dots(10)$$

267
$$S_{time}(W)|_s = (W_n(s) * c_2 \Pi(0.6s))_n \dots\dots\dots(11)$$

268 Where c_1 and c_2 are normalization constants and n is the rectangle function. The factor of 0.6 is
 269 empirically determined scale decorrelation length of the Morlet wavelet (Torrence and Compo,

270 1998). The statistical significance level of the wavelet coherence is estimated using the Monte
271 Carlo methods (Grinsted et. al., 2004).

272

273 **4. Results and Discussion:**

274 We analyzed the data sets spanning over the period of 1876-2000 using the PCA, SSA and
275 wavelet spectral analyses. Figure 1 shows four time series: (1) Smoothed Sunspot number
276 representing solar activities; (2) Geomagnetic (aa indices); (3) Troup Southern Oscillation Index
277 (SOI) for the study of ENSO and (4) Western Himalayan temperature variability record that are
278 analyzed in the present work. From visual inspection it is apparent from Fig. 1 that both WH
279 and SOI data show irregular and random pattern, while sunspot numbers have quasi- cyclic
280 character. Further WH tree ring record also exhibits distinct temperature variability but
281 nonstationary behavior at different scales. This variability might be suggestive of coupled
282 global ocean-atmospheric dynamics or some other factors, such as deforestation,
283 anthropogenic, high latitudinal influence etc (Yadav et. al., 2004).

284

(Figure 1)

285 Hence it is quite difficult to differentiate such a complex climate signals visually and difficult to
286 infer any clear oscillation without the help of powerful mathematical methods. For
287 identification of any oscillatory components and understanding the climatic variations on
288 regional and global scale, we have applied the PCA, SSA and wavelet analysis. Figure 2 shows
289 the principal components (PCs) for the first four eigen triples (PC1, PC2, PC3, PC4) for the given
290 data sets. Figure 3 shows the power spectra of the principal components (PCs) for the four data
291 sets shown in figure 2. From the figure 3, it is observed that the power spectra of PC1-4 for the
292 sunspot data exhibits high power at 124, 11, 4-2.8 years. The presence of high solar signal at
293 124 years indicates the quasi-stable oscillatory components in the data. The power spectra of
294 geomagnetic data also shows the presence of strong signals at 124, 10-11, 4-2 years suggesting
295 a strong link of solar-geomagnetic activity. The power spectra of WH temperature data shows
296 strong high power at ~62 years, 32-35 years, 11 years, 5 years and 2-3 years suggesting a
297 strong influence of solar-geomagnetic-ENSO effects on the Indian climate system. Dominant

298 amplitude is found at 32-35 years corresponding to AMO cycles. These results can be better
299 confirmed by applying the mathematical tools of SSA and wavelet analysis.

300 **(Figure 2 & 3)**

301 To explore the stationary characteristics of these peaks obtained by the PCA, we have applied
302 the Morlet based wavelet transform approach (Holschneider, 1995; Foufoula-Georgiou and
303 Kumar, 1995; Torrence and Compo, 1998; Grinsted et. al., 2004). The wavelet spectrum
304 identifies the main periodicities in the time series and helps to analyze the periodicities with
305 respect to time. Figure 4 shows the wavelet spectrum for the a) Smoothed Sunspot number for
306 solar activity (SSN) (b) Western Himalayan (WH) temperature variability record (c) Geomagnetic
307 activity and (c) Troup Southern Oscillation Index (SOI). From the wavelet spectrum of sunspot
308 time series (Figure 4a), the signal near 11-year is the strongest feature and is persistent during
309 the entire series indicating the non-stationary behavior of the sunspot time series. The wavelet
310 spectrum of SOI (figure 4c) shows strong amplitudes but nonstationary in the interval of 2- 8
311 years. The wavelet power spectrum of the western Himalayan temperature variability (Figure
312 4b) reveals significant power concentration at inter-annual time scales of 3-5 years and at 11
313 years solar cycle. A dominant amplitude modes is also seen in the low frequency range at
314 around 35-40 years (at periods 1930-1980) corresponding to AMO cycles. Our result agrees well
315 with the results of other climate reconstructions (Mann et. al., 1995) from tree rings and other
316 proxies. The observed variability in AMO periodicity has also been reported in other tree ring
317 record (Gray et. al., 2004). The statistical significance of the wavelet power spectrum is tested
318 by a Monte Carlo method (Torrence and Compo, 1998). The WH spectra depicting statistically
319 significant powers at around 5 years, 11 years and 33 years above the 95% significance level,
320 suggests a clear picture of the imprint of sunspot-geomagnetic and ENSO on the tree ring data.
321 The wavelet power spectrum of the geomagnetic record (Fig. 4d) indicates significant power on
322 shorter scales around 2, 4-8, 11 years period.

323 **(Figure 4)**

324 In order to have better visualization of similar periods in two time series and for the
325 interpretation of the results, cross wavelet spectrum has been applied. Figure 5 shows the cross
326 wavelet spectrum of the a) SSN-WH temperature data b) WH data-SOI and c) SSN-SOI data. The

327 contours (dark black lines) are the enclosing regions where wavelet cross power is significantly
328 higher, at 95% confidence levels. The wavelet cross-spectra of WH-SSN (Fig.5a) show
329 statistically significant high power over a period of 1895-1985 in 8-16 years band. It is seen that
330 the WH-SOI cross-spectra (Fig. 5b), the high power is observed at 2–4 year band and 8–16 years
331 as well. The SSN-SOI spectra (Fig. 5c) shows a strong correlation at 11 years solar cycle, which is
332 stronger during 1910-1950 and 1960-2000 (Rigozo et. al., 2002, Rigozo et. al., 2003) suggesting
333 the strongest El Nino and La Nina events indicating solar modulation on ENSO. These results
334 show a good correspondence in response of growth of the tree ring time series during the
335 intense solar activity. Hence the results strongly support the possible origin of these
336 periodicities from Solar and ENSO events. The interesting conclusion from Fig. 5 is that WH–
337 sunspot connections are strong at 11 years, ENSO–sunspot also exhibit strong power around 11
338 years; the WH–ENSO connections are spread over three bands, the 2–4 y; 4–8 and 8–16 y,
339 covering the solar cycle and its harmonics; the WH-geomagnetic exhibits strong connections
340 around 2-4, 4-6, 11 years and 35-40 years indicating the influence of solar-geomagnetic activity
341 on Indian temperature.

342 **(Figure 5)**

343
344 The Singular spectral analysis (SSA) is performed for all the four data sets with window length of
345 40. The SSA spectra with 40 singular values and its corresponding reconstructed series (varying
346 from RC1-15 in some cases) are plotted are shown in Figure 6 &7. The important insights from
347 SSA spectra are the identification of gaps in the eigen value spectra. As a rule, the pure noise
348 series produces a slowing decreasing sequence of singular values. The explicit plateau in the
349 spectra represents the ordinal numbers of paired eigen triples. The eigen triples 2-3 for the
350 sunspot data corresponds to 11 years period; eigen triples for 1-2,3-5,6-10,11-14 for the WH
351 temperature data are related to harmonic with specific periods (periods 33-35, 11, 5, 2); eigen
352 triples for 2-5,6-9,10-13 for the geomagnetic data are related to periods 11, 5,2 years. The
353 eigen triples for the SOI data represents to ~ 5-7, 2 years periods. In order to assess
354 periodicities, the periodogram and the wavelet power spectra are plotted using the SSA
355 reconstructed data (SSA-RC) (Figure 8). From the figure 8, the periodogram of SSA-RC of SSN

356 and Geomagnetic data shows strong power at ~120, 10-11 years; the SOI data shows strong
357 peaks at 6-9, 3, years & WH data shows strong power at ~32, ~10-11, 3-5 years. The wavelet
358 spectra for all the SSA-RC data confirms the results excepts for periods at ~120 years as the
359 scaling period for the wavelet spectra is 64 years period. The coherency plot of the SSA-RC data
360 sets (Figure 9) indicates a significant power at 33 years, 11 years, 2-7 years in the WH
361 temperature record suggesting the possible influences of Sunspot-geomagnetic activity and
362 ENSO through tele-connection and hence significant role of these remote internal oscillations of
363 the atmosphere-ocean system on the Indian climate system. Researchers have attributed these
364 phenomena to internal ocean dynamics and involve ocean atmospheric coupling as well as
365 variability in the strength of thermohaline circulations (Knight et. al., 2005; Delworth and Mann,
366 2000).

367 **(Figures 6, 7, 8 & 9)**

368 In general our result agrees well with earlier findings in sense that statistically significant
369 global cycles of coupled effects of Sunspot/geomagnetic and ENSO are present in the land
370 based temperature variability record. However, there are certain striking features in the spectra
371 that need to be emphasized regarding the western Himalayas temperature variability: i) Inter-
372 annual cycles in period range of 3-8 years corresponding to ENSO in the wavelet spectra exhibit
373 intermittent oscillatory characteristics throughout the large portion of the record (Fig 4); ii) The
374 11 years solar cycle in the cross wavelet spectrum of SSN and SOI (Figure 5) indicate the solar
375 modulation in the ENSO phenomena. iii) The high amplitude at 11 years in the time intervals
376 1900-1995 with a strong intensity from 1900-1995 shows a good correspondence with the high
377 temperature variability for the interval of high solar-geomagnetic activity. The Multi-decadal
378 (30-40 years) periodicity identified here in Western Himalayan tree ring temperature record
379 matches with North Atlantic sea surface temperature variability implying that the temperature
380 variability in the western Himalayan is not a regional phenomenon, but a globally tele-
381 connected climate phenomena associated with the global ocean-atmospheric dynamics system
382 (Tiwari & srilakshmi, 2009; Delworth et. al., 1993; Stocker, 1994). The coupled ocean-
383 atmosphere system appears to transport energy from the hot equatorial regions towards
384 Himalayan territory in a cyclic manner. These results may provide constraints for modeling of

385 climatic variability over the Indian region and ENSO phenomena associated with the
386 redistribution of temperature variability. The solar-geomagnetic effects play a major role in
387 abnormal heating of the land surface thereby indirectly affects the atmospheric temperature
388 gradient between the land-ocean coupled systems. In the present work, the connections
389 between solar/geomagnetic activity and ENSO on the WH time series are found to be
390 statistically significant, especially when they are studied over contrasting epochs of
391 respectively high and low solar activity. The correlation plots for the SSA-RC data sets of WH-
392 sunspot, WH-aa index, WH-SOI and Sunspot-aa index are plotted in figure 10. It is noticed that
393 there is a correlation plots for the Geomagnetic-sunspot activity has a maximum correlation
394 value at 1 year lag suggesting the strong influence of sunspot & geomagnetic forcing on one
395 another. The cross-correlation plot for the WH data and the SOI represents a maximum value at
396 zero lag. The correlations plot for WH-sunspot & WH-geomagnetic index exhibits almost the
397 identical results suggesting the possible impact of solar activities on the Indian temperature
398 variability.

399 **(Figures 10)**

400 The net effect of solar activity on temperature record therefore appears to be the result
401 of cooperating or counteracting influences of earth's magnetic activity on the shorter and
402 longer periods, depending on the indices used; scale-interactions, therefore, appear to be
403 important. Nevertheless, the link between Indian climate and solar/geomagnetic activity
404 emerges as having the strong evidence; next is the ENSO-solar activity connection.

405

406 **5. Conclusions:**

407 In the present paper, we have studied & identified the periodic patterns from the published
408 Indian temperature variability records using the modern spectral methods. This study of
409 Singular spectral analysis (SSA)-Wavelet spectral methods on the data sets and the application
410 of wavelet analysis for the SSA reconstructed time series highlights the removal of noise in the
411 data and identifies the existence of a high-amplitude, recurrent, multi-decadal scale patterns
412 that are present in Indian temperature records. The Wavelet spectral analysis of SSA
413 reconstructed data identifies significant peaks around 33 years, 11 years, 2-7 years (95%

414 confidence) in the Western Himalayan (WH) temperature record. The presence of 33-year cycle
415 periodicity suggests the Sun-temperature variability probably involving the induced changes in
416 the basic state of the atmosphere. The 30-40 yrs periodicity in Western Himalayan tree ring
417 temperature record matches with the global signal of the coupled ocean-atmospheric
418 oscillation (Delworth et. al., 1993; Stocker, 1994) implying that the temperature variability in
419 Himalayan is not a regional phenomenon, but seems to be tele-connected phenomena with the
420 global ocean-atmospheric climate system. The coherency plots of the SSA reconstructed WH-
421 Sunspot; WH-geomagnetic and WH-SOI data sets show strong spectral signatures in the whole
422 record confirming the possible influences of Sunspot-geomagnetic activities and ENSO through
423 teleconnection and hence the significant role of these remote internal oscillations of the
424 atmosphere-ocean system on the Indian temperatures. We conclude that the signature of
425 solar-geomagnetic activity affects the surface air temperatures of Indian subcontinent.
426 However, long data sets from the different sites on the Indian continent are necessary to
427 identify the influences of the 120 years solar-geomagnetic cycles.

428

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436

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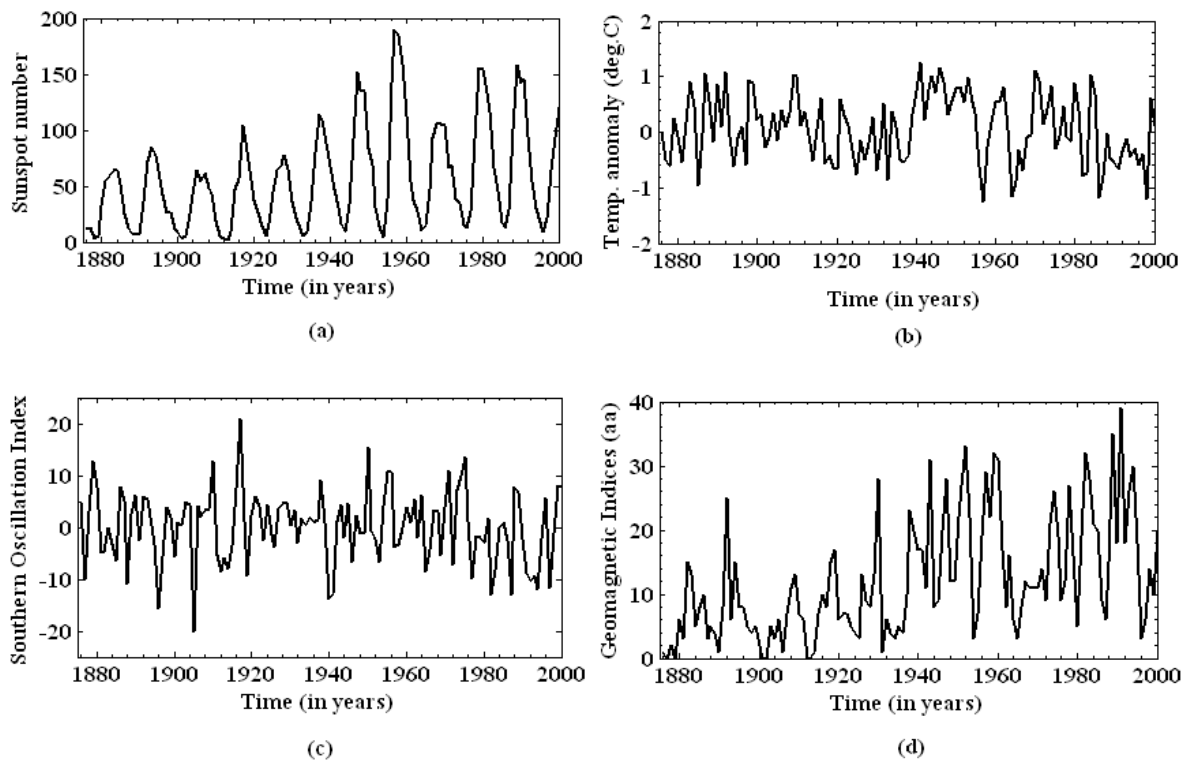
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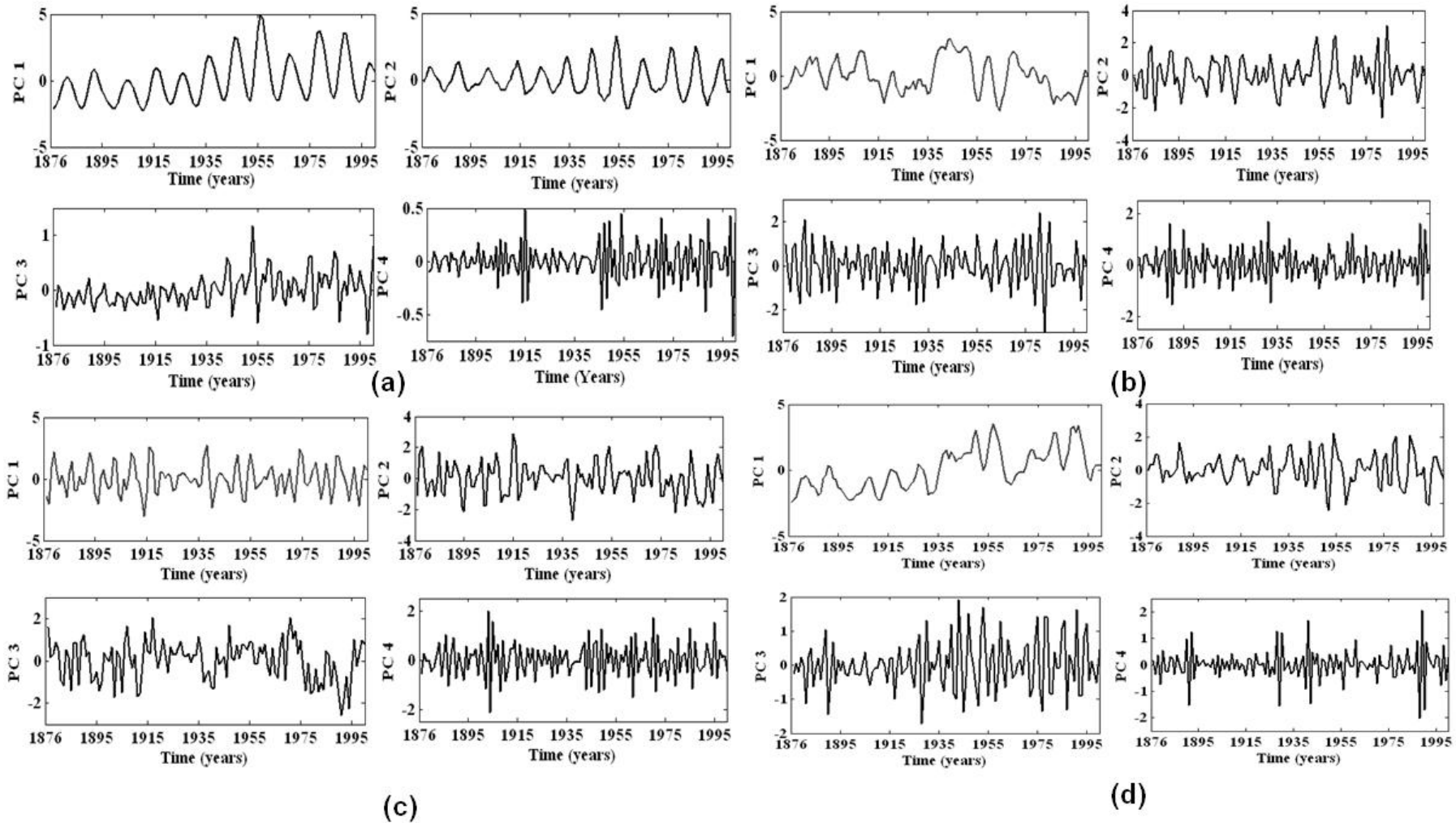


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617 **Figure 1. Time series data of (a) Sunspot Index (b) the mean pre-monsoon temperature**
618 **anomalies of the Western Himalayas (c) Southern Oscillation Index (SOI) and (d)**
619 **Geomagnetic Indices (aa indices) for common period 1876-2000.**

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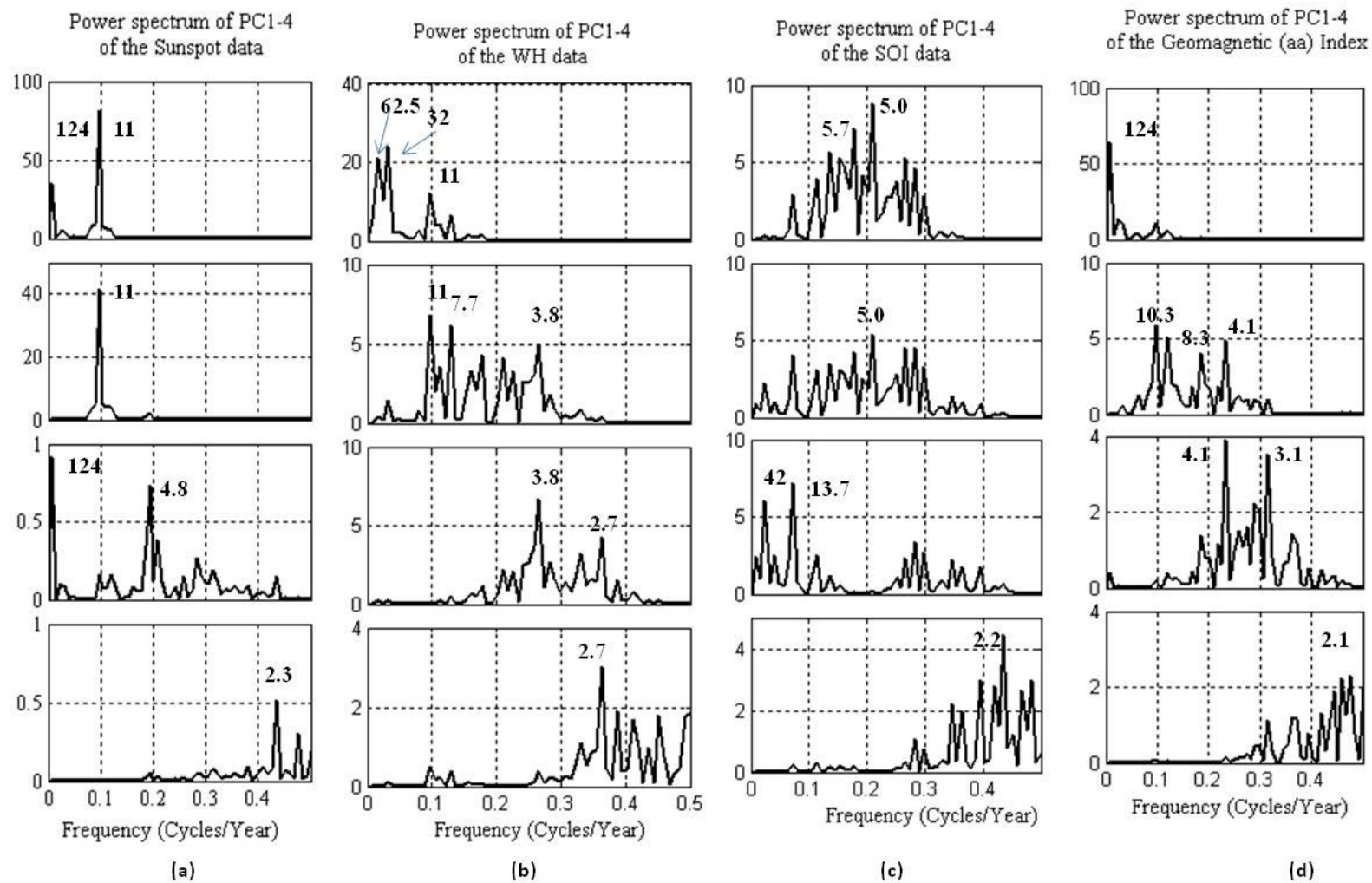


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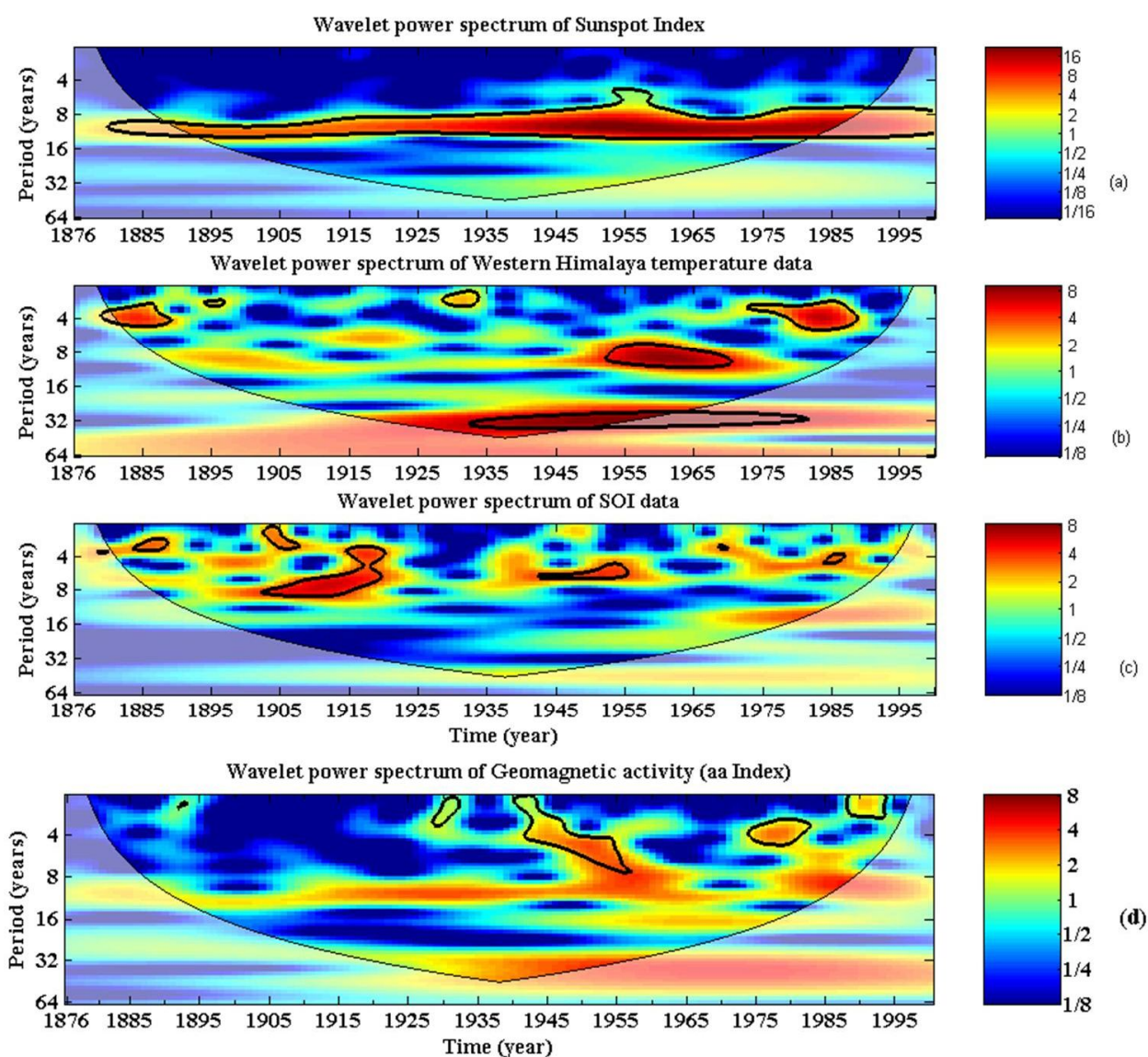
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Figure 2. First four principal components (PCs:1-4) for time series (a) Sunspot numbers (b) the mean pre-monsoon temperature anomalies of the Western Himalayas (c) SOI index and (d) Geomagnetic Indices (aa indices) for the period 1876-2000.



625

626 Figure 3. Power spectra of the first four principal component (PCs) (PC1-4 shown in Fig. 2) for all the data sets with their significant
 627 periodicities at 124, 11, 4 and 2.8 years are indicated in bold letters.

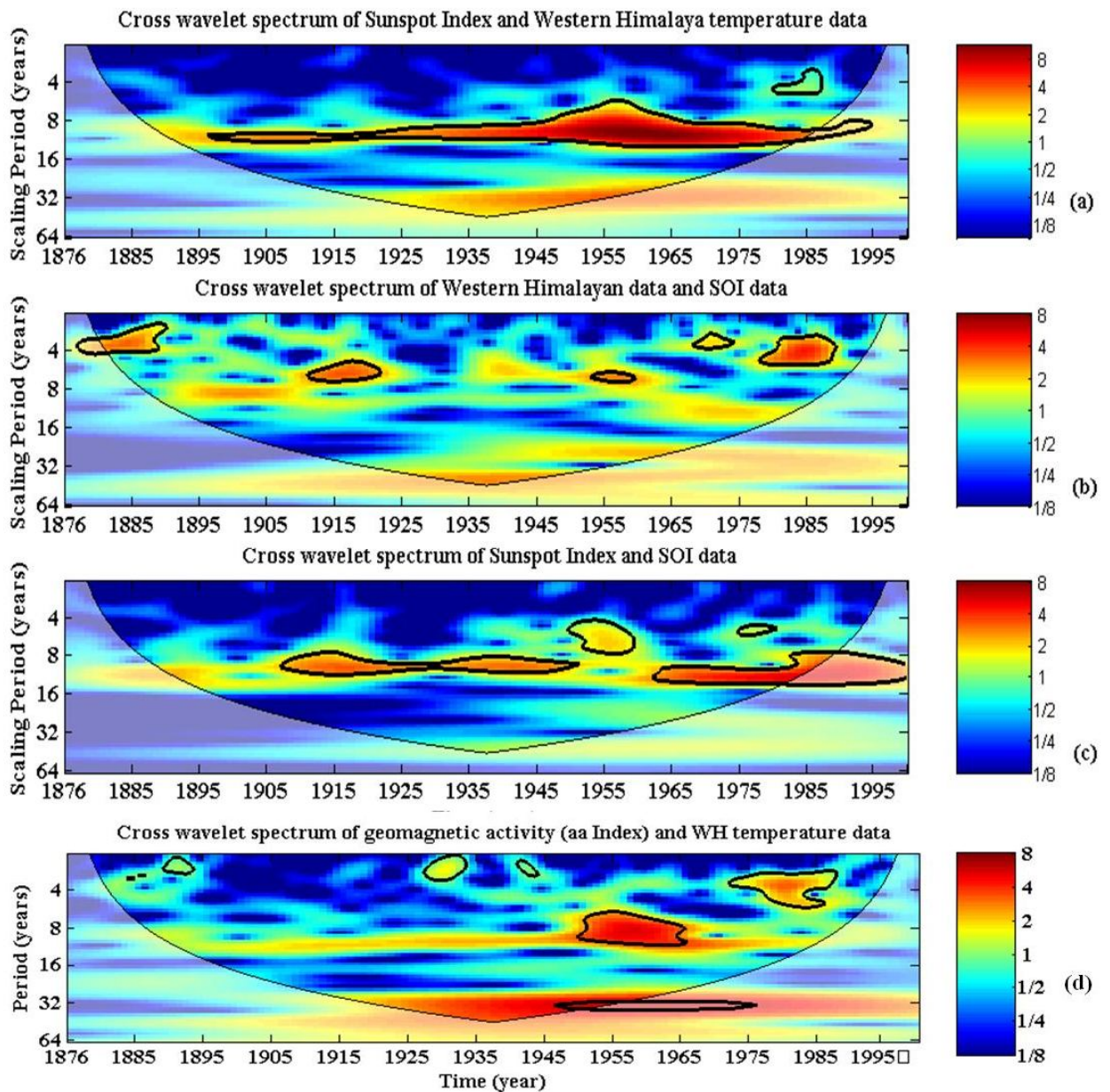


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629 **Figure 4. Wavelet power spectrum of (a) Sunspot Number (b) Western Himalaya temperature**
 630 **data (c) Southern Oscillation Index (SOI) and (d) Geomagnetic activity (aa Indices) with cone**
 631 **of influence (lighter shade smooth curve) and black lines indicate significant power on 95%**
 632 **level compared to red noise based on first order auto-regressive (AR(1)) coefficient. The**
 633 **legend on right indicates the cross-wavelet power.**

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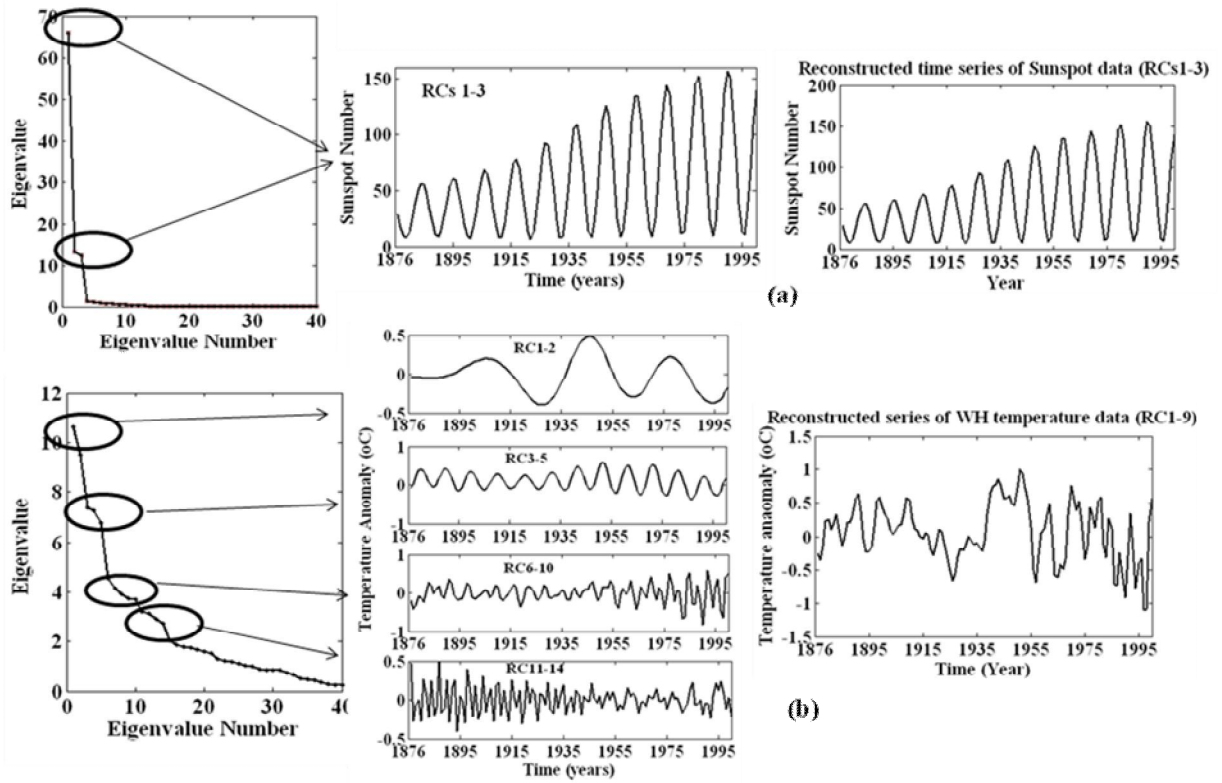
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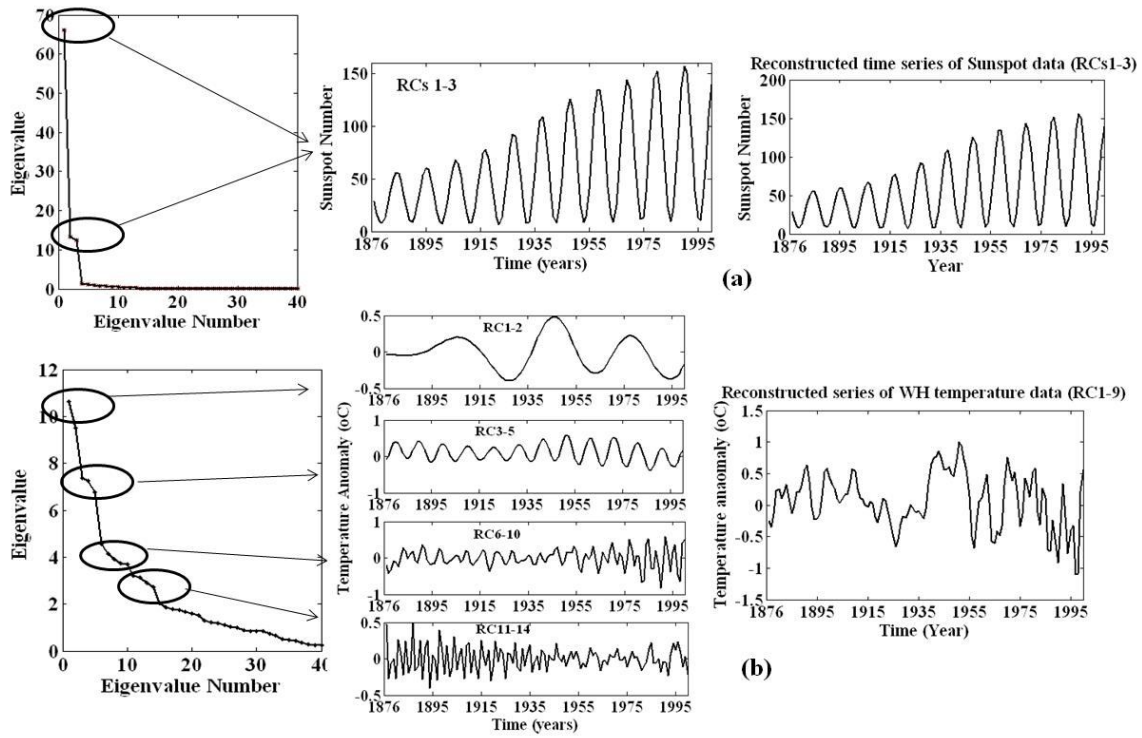
Figure 5. Cross Wavelet spectrum between (a) Sunspot number-Western Himalayan data (b) Western Himalayan-Southern Oscillation Index (c) Sunspot number- Southern Oscillation Index and (d) Geomagnetic: aa indices-Western Himalayan data with cone of influence (lighter shade smooth curve) and black lines indicate significant power on 95% level compared to red noise based on AR(1) coefficient. The legend on right indicates the cross-wavelet power.



643

644 **Figure 6. Singular spectra with its SSA decomposed components & its reconstructed time**
 645 **series for (a) Sunspot Number and (b) Western Himalaya temperature data.**

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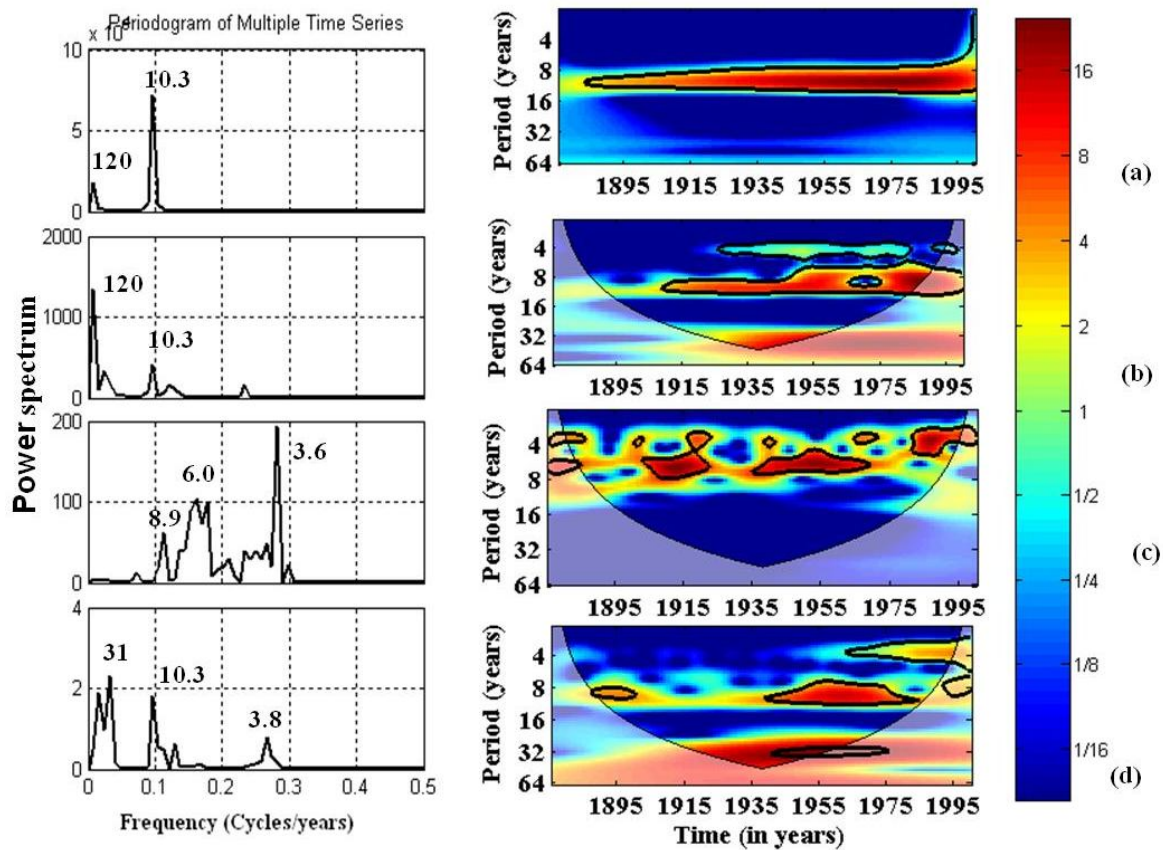


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Figure 7. Singular spectra with its SSA decomposed components & its reconstructed time series for (c) SOI and (d) Geomagnetic activity (aa Indices).



650

651 **Figure 8. Power spectrum and Wavelet power spectrum of SSA reconstructed (a) Sunspot**
 652 **data (b) Geomagnetic Indices (aa index) (c) SOI index and (d) the Western Himalayas**
 653 **temperature data with cone of influence (lighter shade smooth curve) and black lines indicate**
 654 **significant power on 95% level compared to red noise based on AR(1) coefficient. The legend**
 655 **on right indicates the cross-wavelet power.**

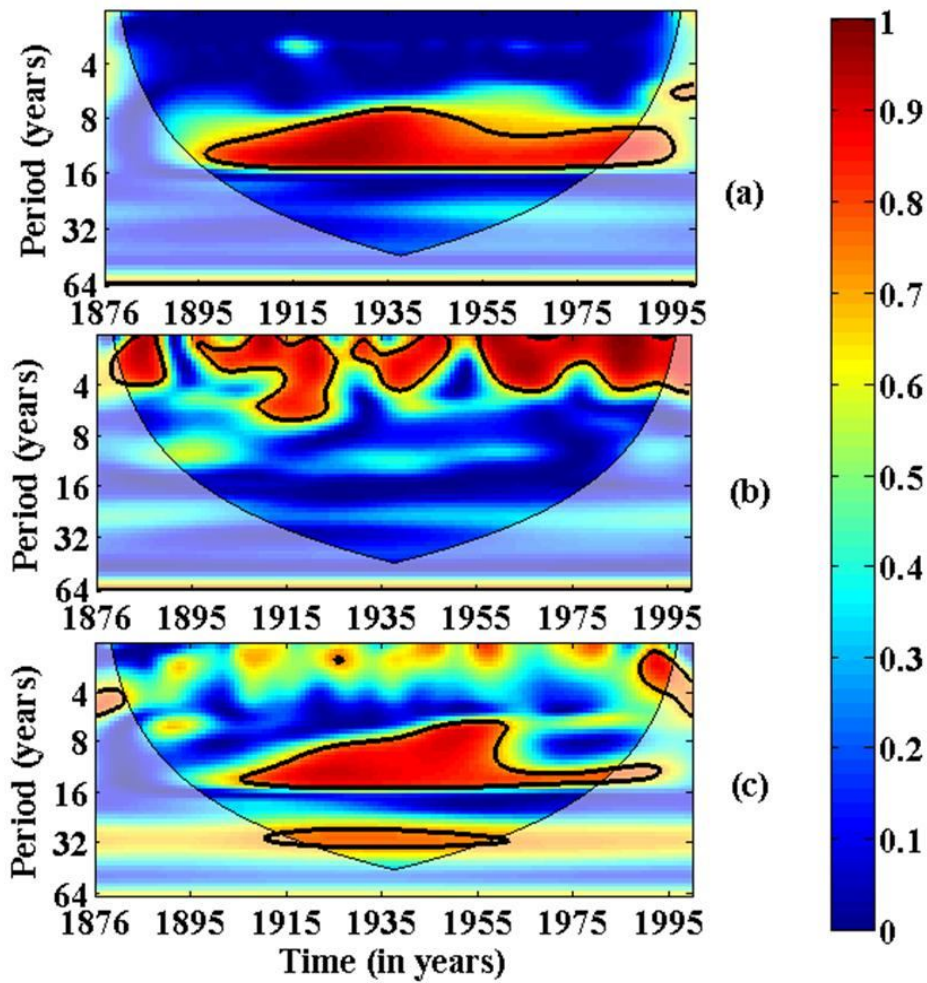
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662 **Figure 9. Squared wavelet coherence plotted for the SSA reconstructed time series between**
 663 **(a) WH-SSN (b) WH-SOI and (c) WH-aa index with cone of influence (lighter shade smooth**
 664 **curve) and black lines indicate significant power on 95% level compared to red noise based on**
 665 **AR(1) coefficient.**

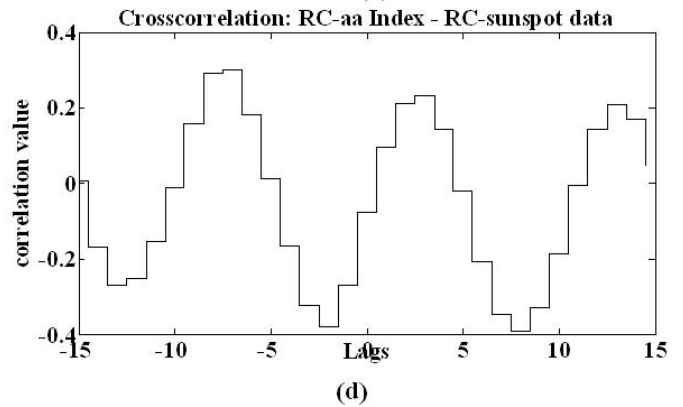
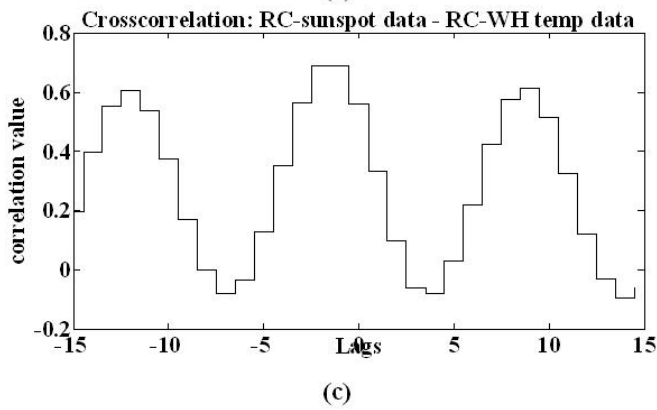
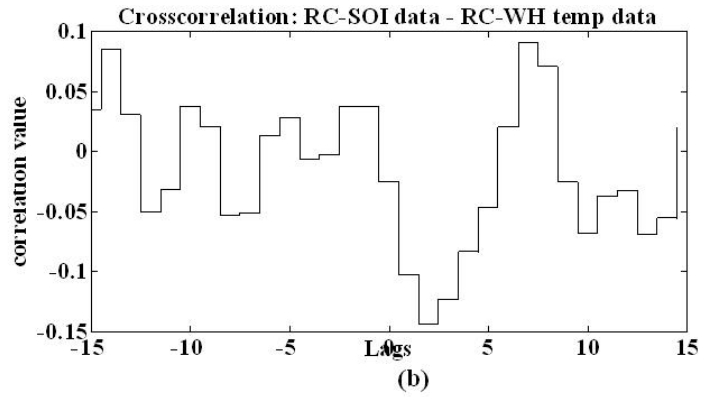
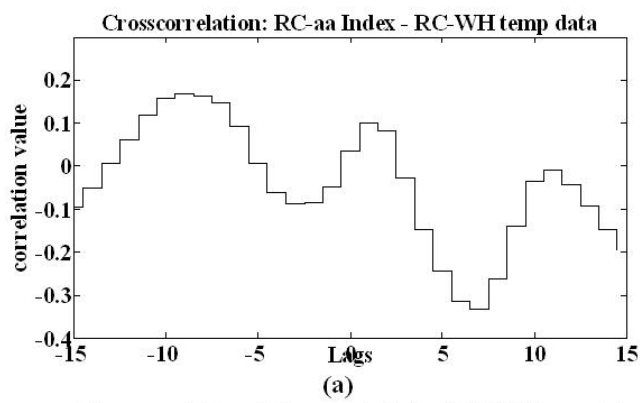
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672 **Figure 10. Cross-correlation of SSA reconstructed time series of (a) aa Index-Western**
 673 **Himalayan (WH) temperature data; (b) SOI-WH temperature data; (c) sunspot -WH data and**
 674 **(d) aa Index-sunspot data.**

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