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Research paper

Sunspots and ENSO relationship using Markov method

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ABSTRACT

The various techniques have been used to confer the existence of significant relations between the number of Sunspots and different terrestrial climate parameters such as rainfall, temperature, dewdrops, aerosol and ENSO etc. Improved understanding and modelling of Sunspots variations can explore the information about the related variables. This study uses a Markov chain method to find the relations between monthly Sunspots and ENSO data of two epochs (1996–2009 and 1950–2014). Corresponding transition matrices of both data sets appear similar and it is qualitatively evaluated by high values of 2-dimensional correlation found between transition matrices of ENSO and Sunspots. The associated transition diagrams show that each state communicates with the others. Presence of stronger self-communication (between same states) confirms periodic behaviour among the states. Moreover, closeness found in the expected number of visits from one state to the other show the existence of a possible relation between Sunspots and ENSO data. Moreover, perfect validation of dependency and stationary tests endorses the applicability of the Markov chain analyses on Sunspots and ENSO data. This shows that a significant relation between Sunspots and ENSO data exists. Improved understanding and modelling of Sunspots variations can help to explore the information about the related variables. This study can be useful to explore the influence of ENSO related local climatic variability.

1. Introduction

The average length of a Sunspot cycle is 11.1 years (until now, the largest length known is 14 years and the smallest 9 years: Hassan et al., 2014). Past studies confer the existence of significant relations between the number of Sunspots and various terrestrial climate parameters and even deposition of the sediments in the river (Gray et al., 2010; Lockwood, 2012; Van Oldenborgh et al., 2013; Anderson, 1990, 1992). More specifically, Anderson (1992), Enfield and Cid (1991) and Tudhope et al. (2001) analysed and observed the relationship between solar variability and ENSO with the other driven factors of the Earth's climate. Sunspot number can be one of the explanatory factors of the climatological parameters like NAO and its variations (Kapala et al., 1998), whereas, their relations to ENSO have been shown by Voskresenskaya and Polonsky (1993) and Hurrell (1996). Higginson et al. (2004) and Fink (2005) have already suggested the existence of significant teleconnections between ENSO, solar variability, with the Afro-Asian monsoon system (Higginson et al., 2004; Fink, 2005). The idea for a solar activity cycle-QBO (Quasi-biennial oscillation) coupling has been controversially established (Labitzke and Van Loon, 1988; Salby and Shea, 1991; Sonett et al., 1992). Moreover, Cole et al. (2000) and Ruzmaikin (1999) described that the El Nino occurrence in terms of mean frequency (5.5 years) is twice of the Sunspot cycle (roughly 11-year). Higginson et al. (2004) also relate these two data by leading or lagging behaviours and their periodicities, for example, he indicates that El Nino events tend to occur 2–3 years after and before the peaks of Sunspots, producing average periodicity with roughly half of the length of the solar cycle. Brugnara et al. (2013) has provided quantified analyses to explain the influence of Sunspot activity from the impact of other known factors (e.g. ENSO, volcanoes) using multiple linear regression methods. Assuming that each predictor involves has a linear relationship with the other predictand.

In view of the above discussion, past studies had quantified the relation between Sunspots and ENSO based on the global attributes like the time leading or lagging and the frequencies. It is not necessary that they apply to all past data intervals. Usually, the

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large-scale circulations affect the local climates and connected phenomena based on their strength of the events (weak, moderate, and strong). Improved understanding and modelling of Sunspots variations can explore the information about the related variables. Markov-chain transition matrix gives the possibility of one state (ranges of values) to next incoming states (ranges of values) (Liu, 2010). This paper analyses the event-based comparison of the Sunspot and the ENSO phenomena using the stochastic Markov chain method. This method is reliable for observing the time-dependent variations of the events.

The Markov chain is a random process that holds transitions from one state to another with the memorylessness property. It means that the probability distribution of the next event (state) depends only on the current state and not on the sequence of events that preceded it. This specific type of "memorylessness" is called the Markov property. It provides the probability between any events defined by the data ranges. The Markov chain process is depending on the transition probability matrix in which probability sum of each row equals to 1. This method could be forecast incoming Sunspot cycles and the corresponding ENSO events. Moreover, different test conditions like stationary, dependency of the data and the correlation test method used for the transition matrices relations are helpful to establish the relation between Sunspots and ENSO data sets. Section 2 deals with the evaluation of transition matrices and their comparison. In the third section, the outcome of the study is presented and the fourth section concludes the study.

2. Material and methods

This study uses a Markov chain method by forming the transition probability matrices of the monthly Sunspots and the ENSO data from 1950–2014 (Fig. 1). Physically, each Sunspot cycle has two major phases, the rising and the falling with respect to the maximum point (the kurtosis) of the cycle (Fig. 1). Each phase is further divided into two parts of the cycle, so they are four parts means four states of equal size. Therefore, this paper considers the four intervals (states) of each type of Sunspots and the ENSO data. Moreover, the interval differences are adjusted according to their data span and to minimise the non-zero communication (non-zero probability) between the states. This study particularly stresses on the forming of transition matrices and the related transition diagram of Sunspot cycle 23 (1996–2009; the last ending cycle). Therefore, at first, the Sunspot monthly data of the cycle 23 and the comparable ENSO data are categorized among the four states

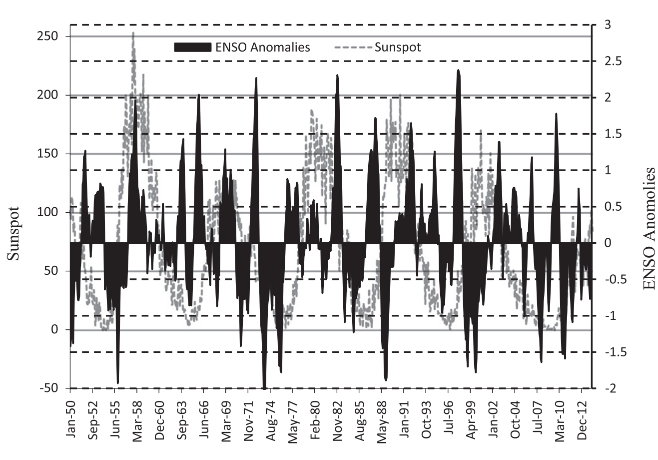

Fig. 1. Time series plot of Sunspots and ENSO monthly data (January 1950–April 2014).

(intervals) as (0–50), (50–100), (100–150) & (150–200) and (−1.78 to −0.58), (−0.58 to 0.62), (0.62–1.82) and (1.82–3.02) respectively. Secondly, the Sunspot data from 1950 to 2014 are categorized as (0–70), (70–140), (140–210) and (210–280) and the corresponding ENSO data as (−2.08 to −0.88), (−0.88 to 0.32), (0.32–1.52) and (1.52–2.72) intervals.

2.1. Markov chain

In the first-order, Markov chain each next state depends only on the state immediately preceding it. Consider a first-order Markov chain with k states $E = \{1, 2, \ldots, k\}$ satisfying the following relationship:

$$P(x_{t+1} = i_{t+1} | x_0 = i_0, \ldots, x_t = i_t) = P(x_{t+1} = i_{t+1} | x_t = i_t) \quad (1)$$

where x_t represent the state of a stochastic time series process (Shamshad et al., 2005)

Generally, for a given sequence of time points $t_1 < t_2 < \cdots < t_{n-1} < t_n$, the conditional probability is defined as

$$P\{x(t_n) = i_n | x(t_1) = i_1, \ldots, x(t_{n-1}) = i_{n-1}\} = P\{x(t_n) = i_n | x(t_{n-1}) = i_{n-1}\} \quad (2)$$

The conditional probabilities $P\{x(t) = j | x(d) = i\} = P_{ij}(d, t)$ are called transition probabilities of order $r = t - d$ from state i to state j for all $0 \le d < t$ with $i \ge 1$ and $j \le k$.

2.1.1. Transition probability matrix

The one-step transition probabilities of the Markov chain for a given sequence of time points $t_1 < t_2 < \ldots < t_{n-1} < t_n$, represented as conditional probabilities $P(x_{t+1} = i_{t+1} | x_t = i_t)$ define as

$$p_{ij} = P(x_{t+1} = j | x_t = i) \quad \text{for} \quad i, j \in E \quad (3)$$

The transition probability matrix is denoted by P. For states k, the first order transition matrix P has a size of $k \times k$ and takes the form:

$$P = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,k} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,k} \\ \cdots & \cdots & \cdots & \cdots \\ p_{k,1} & p_{k,2} & \cdots & p_{k,k} \end{bmatrix}$$

From the relative frequencies of the k states we can estimate state probabilities at time t. The number of transitions from state i to state j is denoted by n_{ij}. The transition probabilities are defined as

$$p_{ij} = \frac{n_{ij}}{\sum_j n_{ij}} \quad (4)$$

This one-step transition matrix $P = (p_{ij})_{k \times k}$ must satisfy the following two properties:

$$0 \le p_{ij} \le 1 \quad \sum_{j=1}^{k} p_{ij} = 1 \quad \forall\, i, j \in E \quad (5)$$

2.1.2. Expected number of visits

The two states belong to the same communication class if the end of the first state is the starting point of the second. If all states communicate one another, then the transition matrix has one communication class and it is called as an irreducible matrix (Brown and Ross, 1969). A state i is transient if with the probability 1 the chain visits only i finite number of times. A state i is recurrent if with the probability 1 the chain visits only i infinite number of times. A Markov chain starting with a recurring class never leaves that class (Lawler, 2004).

The transient matrix represented by P is define as

$$P = \begin{bmatrix} \overline{P} & 0 \\ S & Q \end{bmatrix} \quad (6)$$

where the matrix P has some transient sub matrix Q, which includes only rows and columns for the transient states. If P is a reducible Markov chain, then it has at least one recurrent class or classes$(\overline{P})$, which consider only rows and columns for states in $\overline{P}$ (Lawler, 2004).

The expected number of visits to i starting at j is given by M_{ji} where $M = (I - Q)^{-1}$. An overall, transient state is the expected number of steps until the chain enters a recurring class (such that $X_0 = j$). This technique can be used for irreducible Markov chains (Lawler, 2004).

2.2. Validity of Markov chain

The applicability of the Markov chain method for Sunspots and ENSO analyses is validated by the dependency and stationary tests of the corresponding data (Shamshad et al., 2005).

2.2.1. Dependency test

Dependency of events confirms the applicability of Markov chain method (Torre et al., 2001; Logofet and Lensnaya, 2000). The test statistic α determines the independence of the successive events and it is asymptotically distributed as χ^2(Chi-squared) with $k - 1$ degrees of freedom where k is the total number of states. The test statistic α is defined by

$$\alpha = 2 \sum_{i,j}^{k} n_{ij} \ln \frac{p_{ij}}{p_j}$$

where $p_j$is the marginal probability of j^{th} column of transition matrix, and is defined as:

$$p_j = \frac{\sum_i^m n_{ij}}{\sum_{i,j}^m n_{ij}}$$

where n_{ij} is the frequency in state i followed by state j.

For $\alpha > \chi^2$in 5% level, we reject the null hypothesis that the successive transition is independent. It is concluded that transition of monthly Sunspot and ENSO data has the first order Markov chain property.

2.2.2. Temporal stationary test

If the transition probabilities do not depend on time, then a Markov chain is said to be stationary. Test statistic β defined by

$$\beta = 2 \sum_{1}^{T} \sum_{ij}^{k} n_{ij}(t) \ln\left[\frac{p_{ij}(t)}{p_{ij}}\right]$$

is used to test the stationary, where T is the number of time intervals, $n_{ij}(t)$ represent the frequencies of the tally matrix and $p_{ij}(t)$ is the transition probabilities of the matrix. β should have a χ^2 (Chi-squared) distribution with $K(K-1)(T-1)$ degrees of freedom. For $\beta < \chi^2$the process is stationary in a 5% confidence interval (Shamshad et al., 2005).

3. Results and discussions

The four transition probability matrices of two different ranges (1996–2009 and 1950–2014) of Sunspots and ENSO data are formed. To keep the size of classes equal all data sets are divided into four states as defined in Section 2.

In the first phase, this study evaluates transition probabilities of monthly Sunspots and ENSO data from 1996- to-2009. The corresponding transition matrices (Tables 1a and b) of both data series show higher probability values appear on the main diagonal except the value laying in 4th state of Sunspot matrix. These higher values confirm the strong self-communication and periodic behaviour in both data series. Moreover, the associated transition diagrams (Fig. 2a and b) display similar patterns of communication from one state to another. The 2-Dimensional correlation value of 0.5897 between transition matrices of Sunspots and ENSO (1996–2009) persistent relatively strong relation.

The average number of steps needed for each state to reach the other states (Fig. 2) is known as the expected number of visits and is determined by Markov chain method. Table 2 compares the

Table 1
(a) Transition matrix of Sunspots data 1996–2009 (cycle-23). (b) Transition matrix of ENSO data 1996–2009.

(a)	States	1	2	3	4
	1	0.94118	0.058824	0	0
	2	0.125	0.65	0.225	0
	3	0	0.33333	0.59259	0.074074
	4	0	0	1	0
(b)	**States**	**1**	**2**	**3**	**4**
	1	0.875	0.125	0	0
	2	0.08	0.86667	0.053333	0
	3	0	0.16	0.8	0.04
	4	0	0	0.16667	0.83333

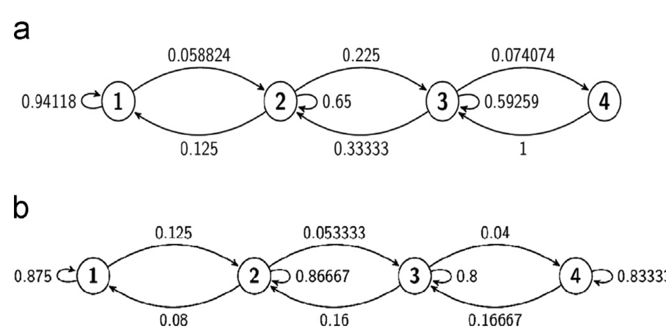

Fig. 2. Transition diagram (1996–2009) where 1, 2, 3, and 4 corresponds the states for (a) Sunspots data (cycle-23) and (b) ENSO data.

Table 2
Comparison of expected number of visits (in months and years) among states of 23rd Sunspots cycle and appropriate ENSO. Both types of visits shows the difference between the states increases then number of steps will also increases. Bold values depict the maximum number of visits of the reference state.

Transition (→) from reference state to another	No of steps (months)		No of steps (years)	
	Sunspot	**ENSO**	**Sunspot**	**ENSO**
1 → 2	17.0010	8.0000	1.41675	0.66667
1 → 3	30.8919	38.7520	2.57433	3.22933
1 → 4	**106.9111**	**186.8013**	8.90926	15.56678
2 → 1	13.7995	17.6729	1.14996	1.47274
2 → 3	13.8900	30.7520	1.15750	2.56267
2 → 4	**89.9039**	**178.8013**	7.49199	14.90011
3 → 1	17.0215	25.4215	1.41846	2.11846
3 → 2	3.2222	7.7500	0.26852	0.64583
3 → 4	**76.0112**	**148.0410**	6.33427	12.33675
4 → 1	18.0215	31.4158	1.50179	2.61798
4 → 2	4.2222	13.7499	0.35185	1.14583
4 → 3	**1.0000**	**5.9999**	0.08333	0.49999

expected visit for Sunspots and corresponding ENSO data (monthly and yearly). The number of values in state 4 proceeding from the states 3, 2 and 1 are step by step increases and reaches the largest number of visits from state 1 to 4, observed in both Sunspot and ENSO data (Table 2). The expected visit of Sunspots and ENSO data from state 4 to 3 has the least value compared to any other values in Table 2. It is also noted that as the state numbers (address) deviates large from reference state the expected number of visit increases for both the Sunspots and ENSO data.

To check the validity of the Markov chain method on both types of data sets (1996- to-2009) dependency and stationary test is applied as defined in Section 2.2. For the dependency an α test is applied (Section 2.2.1). The test values α_1 (166.1902) for Sunspot data and α_2 (206.4682) of corresponding ENSO data are achieved and both are higher ($\alpha > \chi^2$) than their chi squared values χ_1^2 (85.8214) and χ_2^2 (109.1518) respectively. To check the stationarity of each data series a β test is applied. The test values β_1(9.60092) of the Sunspot 23rd cycle and β_2(6.13276) of corresponding ENSO data are evaluated. Both beta values are smaller than their corresponding chai-squared χ_1^2 (85.8214) and χ_2^2 (109.1518) values respectively. This agreed with the stationary test relation $\beta < \chi^2$ discussed in Section 2.2.2.

In the second part, same analyses are performed for Sunspots and ENSO data from 1950 to 2014 (Fig. 1). The resemblance between the Sunspots and ENSO (1950–2014) transitions matrix element values (Table 3) and diagrams (Fig. 3) are preserved. The transient matrices and their diagrams of both data are depicted in Table 3 and Fig. 3 reveals the similar formation of values and tracks as occurred in Table 1 and Fig. 2 of both data series of 1996- to-2009 range. Moreover, a 2-dimensional correlation value of 0.9518 evaluated between transition matrices of Sunspots and ENSO (1950-2014) shows their strongest relation. Furthermore, Tables 2 and 4 provide the comparison of the expected number of visits for Sunspots and corresponding ENSO data sets of 1996–2009 and 1950–2014 respectively. Both tables have largest value when they transit from state 1 to 4 and smallest while it goes from state 4 to 3. The return period from any state to state 4 is larger according to the deviation of states. This is in contrast to expected visits from any state to other lower states.

As before, same test of dependency (α test) is applied on Sunspots and ENSO (1950–2014) data for validity of the Markov chain method. In this regards α_3 (803.5096) of Sunspots and α_4 (973.1984) of corresponding ENSO data are evaluated and have larger values ($\alpha > \chi^2$) as compare to their chai-squared values χ_3^2 (107.0618) and χ_4^2 (107.5716) respectively. The results show that significant condition of dependency and stationary for both observed data sustained.

Markov chain analysis confirms that both data set of (1996–2009) and (1950–2014) of two different data series have the same behaviour as regards to the number of steps involved in incoming and outgoing, expected visit for each of the states, and the existence of similar behaviour in the transition matrices & diagrams and their strong 2-dimensional correlation values. Moreover, the validity of dependency and stationary tests confer the applicability of the Markov chain analysis. Above discuss analyses outcomes and the validity tests result explores some signatures of Sunspots dependent ENSO variations.

Table 3
(a) Transition matrix of Sunspots data 1950–2014. (b) Transition matrix of ENSO data 1950–2014.

(a)	States	1	2	3	4
	1	0.93333	0.066667	0	0
	2	0.12987	0.76623	0.1039	0
	3	0	0.28235	0.69412	0.023529
	4	0	0	0.4	0.6
(b)	**States**	**1**	**2**	**3**	**4**
	1	0.75789	0.24211	0	0
	2	0.052632	0.85885	0.088517	0
	3	0	0.16592	0.79821	0.035874
	4	0	0	0.22857	0.77143

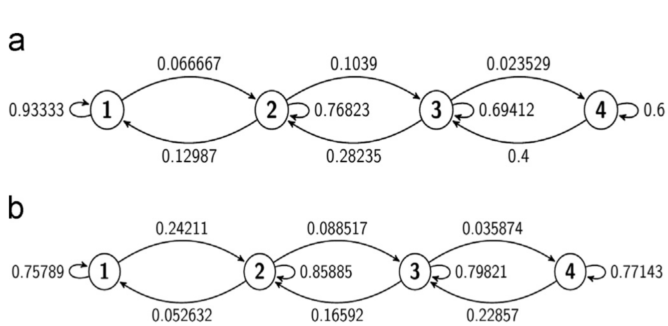

Fig. 3. Transition diagram (1950–2014) where 1, 2, 3, and 4 corresponds the states (a) Sunspots data and (b) ENSO data.

Table 4
Comparison of expected number of visits (in months and years) among states of Sunspots cycle (1950–2014) and appropriate ENSO. Both types of visits shows the difference between the states increases the number of steps will also increases. Bold values depict the maximum number of visits of the reference state.

Transition (→) from reference state to another	No of steps (months)		No of steps (years)	
	Sunspot	ENSO	Sunspot	ENSO
1→2	14.9993	4.1304	1.24994	0.3442
1→3	43.3720	17.8833	3.61433	1.490275
1→4	**426.0159**	**109.3719**	35.50133	9.114325
2→1	10.7002	30.7280	0.89168	2.560667
2→3	28.3687	13.7530	2.36406	1.146083
2→4	**411.0351**	**105.2415**	34.25293	8.770125
3→1	14.4501	37.7018	1.20418	3.141817
3→2	3.7500	6.9731	0.31250	0.581092
3→4	**382.6853**	**91.4892**	31.89044	7.6241
4→1	16.9501	42.0774	1.41251	3.50645
4→2	6.2500	11.3481	0.52083	0.945675
4→3	**2.5000**	**4.3500**	0.20833	0.3625

4. Conclusion

Using Markov chain method, this study explored a strong relation between Sunspots and ENSO according to the resemblance in the formation of the values of the transition matrices, tracks of transition diagram, and found the same formation of the return period values. Moreover, these relations are more confirming with the evaluation of 2-dimensional correlation of 0.5897 and 0.9518 between Sunspots and the ENSO transition matrices of 1996–2009 and 1950–2014 data sets respectively. The above results infer that Sunspots influence the ENSO data. This study can be useful for further investigation of the impact of Sunspot and ENSO related local climatic variability.

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References

Anderson, R.Y., 1992. Possible connection between surface winds, solar activity and the Earth's magnetic field. Nature 358, 51–52.

Anderson, R.Y.,1990. Solar-cycle modulations of ENSO: a possible source of climatic change. In: Sixth Annual Pacific Climate (PACLIM) Workshop , 5–8 March 1989, Asilomar Conference Center, Pacific Grove, CA, pp. 77–81.

Brown, M., Ross, S.M., 1969. Some results for infinite server Poisson queues. J. Appl. Probab. 63, 604–611.

Brugnara, Y., Brönnimann, S., Luterbacher, J., Rozanov, E., 2013. Influence of the sunspot cycle on the Northern Hemisphere wintertime circulation from long upper-air data sets. Atmos. Chem. Phys. 13, 6275.

Cole, J.E., Dunbar, R.B., McClanahan, T.R., Muthiga, N.A., 2000. Tropical pacific forcing of decadal SST variability in the western Indian Ocean over the past two centuries. Science 287, 617–619.

Enfield, D.B., Cid, S.L., 1991. Low-frequency changes in El Phys. 69: 81–100. Nin~o-Southern Oscillation. J. Clim. 4, 1137–1146.

Fink, D., 2005. Multidecadal and century-scale ENSO variability in 20000-year sediment records from the Peru continental margin. Paper Presented at 10th International Conference on Accelerator Mass Spectrometry, University of California, Berkeley, 5 September.

Gray, L.J., Beer, J., Geller, M., Haigh, J.D., Lockwood, M., Matthes, K., Cubasch, U., Fleitmann, D., Harrison, G., Hood, L., Luterbacher, J., Meehl, G.A., Shindell, D., van Geel, B., White, W., 2010. Solar influences on climate. Rev. Geophys. 48 (4).

Hassan, D., Abbas, S., Ansari, M.R.K., Jan, B., 2014. The study of Sunspots and K-index data in the perspective of probability distributions. Int. J. Phys. Soc. Sci. 4 (1), 23–41.

Higginson, M.J., Altabet, M., Wincze, A., Herbert, L., Murray, D. W., T.D., 2004. A solar (irradiance) trigger for millennial-scale abrupt changes in the southwest monsoon. Paleoceanography 19, PA3015. http://dx.doi.org/10.1029/2004PA001031.

Hurrell, J.W., 1996. Influence of variations in extratropical winter-time teleconnections on Northern Hemisphere temperatures. Geophys. Res. Lett. 23, 665–668.

Kapala, A., Mächel, H., Flohn, H., 1998. Behaviour of the centres of action above the Atlantic since 1881. Part II: associations with regional climate anomalies. Int. J. Climatol. 18 (1), 23–36.

Labitzke, K., Van Loon, H., 1988. Associations between the 11 year solar cycle, the QBO, and the atmosphere. Part I: the troposphere and stratosphere in the northern hemisphere winter. J. Atmos. Terr. Phys. 50, 197–206.

Lawler, G.F., 2004. An introduction to the stochastic Loewne revolution. Random Walks Geom., 27–30.

Liu, T., 2010. Application of Markov chains to analyze and predict the time series. Mod. Appl. Sci. 4 (5), 162.

Lockwood, M., 2012. Solar influence on global and regional climates. Surv. Geophys. 33 (3–4), 503–534.

Logofet, D.O., Lensnaya, E.V., 2000. The mathematics of Markov models: what Markov chains can really predict in forest successions. Ecol. Model. 126 (2), 285–298.

Ruzmaikin, A., 1999. Can El Nin~o amplify the solar forcing of climate. Geophys. Res. Lett. 26, 2255–2259.

Salby, M.L., Shea, D.J., 1991. Correlations between solar activity and the atmosphere: an unphysical explanation. J. Geophys. Res.: Atmos. (1984–2012) 96 (D12), 22579–22595.

Shamshad, A., Bawadi, M.A., Hussin, W.W., Majid, T.A., Sanusi, S.A.M., 2005. First and second order Markov chain models for synthetic generation of wind speed time series. Energy 30, 693–708.

Sonett, C.P., Williams, C.R., Mörner, N.A., 1992. The Fourier spectrum of Swedish riverine varves: evidence of sub-arctic quasi-biennial (QBO) oscillations. Palaeogeogr. Palaeoclim. Palaeoecol. 98 (1), 57–65.

Torre, M.C., Poggi, P., Louche, A., 2001. Markovian model for studying wind speed time series in Corsica. Int. J. Renew. Energy Eng. 3 (2), 311–319.

Tudhope, A.W., Chilcott, C.P., McCulloch, M.T., Cook, E.R., Chappell, J., Ellam, R.M., Shimmield, G.B., 2001. Variability in the El Niño-Southern Oscillation through a glacial-interglacial cycle. Science 291 (5508), 1511–1517.

Van Oldenborgh, G.J., De Laat, A.T.J., Luterbacher, J., Ingram, W.J., Osborn, T., 2013. Claim of solar influence is on thin ice: are 11-year cycle solar minima associated with severe winters in Europe? Environ. Res. Lett. 8 (2), 024014.

Voskresenskaya, E.N., Polonsky, A.B., 1993. Air pressure fluctuations in the North Atlantic and their relationship with El Nin~o-southern oscillations. Phys. Ocean. 4, 275–282.