We would like to thank the referees for taking the time and effort to review our manuscript andfor their positive, constructive and thorough comments. In the revised version of our manuscript we have accommodate all of their remarks.

1st reviewer

1. From the description of the utilized approach for earthquake network construction,it is not clear if the resulting network is considered directed or undirected. Since theconstruction is based on a temporal succession of events in some well-defined direction,a directed network representation appears reasonable. However, in such case,the definition of ACC would not be unique, since different motifs of three nodes wouldbe accounted for. This aspect should be clarified.

Response. The proposed approach results to a directed network. In the appendix we give the definitions of statistical measures for directed networks. For example the first equation in the appendix gives the clustering coefficient for a directed graph, as it is defined byFagiolo, Physical Review E 76, 026107 2007. According to this definition, the clustering coefficient is again the ratio between all directed triangles actually formed by nodeiand the number off all possible triangles that node i could form. This definition gives a natural extension of binary undirected networks. Finally in the case of random graphs the expected mean ACC is p (same as the random undirected networks) where p is the probability that two nodes will be connected.

However reading again the manuscript based on the comment of the reviewer indeed this is not so clearly written. In the revised version we intend to clarify better this issue. We will also add the relevant references for the definition of the ACC for directed networks.

Change.Pag. 5, Lines8-16 and appendix pag.11 lines 14-17.

2. The information provided by the evolving earthquake network analysis in terms ofACC and small-world index can hardly be interpreted without knowledge of the associatedlink density (or, alternatively, mean degree) and its variation with time. Thisinformation needs to be added. Notably, the path length of a network shows an ultimaterelation with the link density, which would be reflected in the small-world index.A similar statement applies to the ACC: if we have a sparse network with low meandegree, the fraction of nodes with degree smaller than 2 can be expected to be largerthan for networks with more edges. Such nodes contribute with a zero term to the calculationof the ACC. Hence, the temporal signatures of ACC reported by the authorscould also trivially reflect different link densities during different time windows. A wayto circumvent this problem would be replacing the ACC by the “network transitivity” orclustering coefficient as defined by Barrat and Weigt, Eur. Phys. J. B, 2000. A comparativediscussion of both measures in terms of evolving networks can be found inRadebach et al., Phys. Rev. E, 2013.

Response. We agree with the reviewer that there is a clear dependency between the link density and the corresponding network measures. For that reason in the manuscript we present also the "fixed number of events"-way of constructing the underlying networks. This fixes the link density to a constant and in this way the effect of the link density is factored out(see e.g. Figure 3, right column). We calculated the mean degree (not shown) in order to perform statistical significance analysis (page 5 line 5-7). Within the period before the main seismic event, we found no significant statistical differences with respect to the mean degree. However we agree with the reviewer that extra information of the link density is required and we will do so in the revised manuscript.

Change. Pag. 6, Lines 31-32, Pag.7, Lines 1-2 and also new figure 7.

3. The authors relate the "more clustered seismicity pattern" identified by ACC to "theemergence of few nodes with higher centrality [supposedly betweenness centrality?],which act as hubs" (p.6, ll.5-6). This is not clear, which can already be seen from theprevious comment.

Response.We agree with the reviewer that this is not so clear. We will clarify better in the revised manuscript taking also into account the previous comment.

Change.Pag. 6,Line. 21-25.

4. It is not clear why network measures are necessary to identify the strong spatialclusteringprior to the L'Aquila mainshock. Couldn't standard methods of spatial statisticsserve the same purpose?

Response. Certainly standard methods of spatial statistics may serve the same target and have been done in previous papers which we cite in our manuscript in section 2. What we propose here is an alternative/complementary way that may facilitate and strengthen our arsenal in accessing strong spatial clustering and identifying "tip" points and particular distinct spatio-temporal patterns in the behavior of the seismicity. One of the relative advantages that come from complex network theory is that networks may be used to identify efficiently, within the nonlinear dynamics theory framework, phase-transitions that mark the onset of big changes in the underlying seismicity. Actually, as we mention in the manuscript, this line of research is motivated by the concept of self-organized criticality (Bak, 1996) which models structural phase transitions from random to scale-free spatial correlations between seismic events (e.g. Sammis and Sornette, 2002). Yet, the generalization and reliability of the outcomes of this relatively new approach remains an open question.The wealth of statistical measures of the reconstructed network activity (such as the small-worldness, path-length, local and global clustering coefficient, betweenness centrality) offers many different views and tools for characterizing the underlying varying topology.

For the particular case, the proposed approach looks promising as identified (retrospectively as all other methods until now) quite efficiently, about two months before the mainshock, the location of the mainshock epicenter.

In the revised version we intend to highlight more these issues in the Discussion Section.

Change.Pag. 8-9, section 5. Discussion

5. The authors claim that "the topological measures appear to outperform other observablesreported in previous statistical work" (p.7, ll.23-24) without clarifying whichprevious variables are meant. No corresponding references are given, nor does themanuscript contain a detailed comparative study for the considered foreshock sequence.

Since the performance statement is repeated twice on p.8, the least to beexpected is further detailed information on this aspect. I also don't think that a comparativeperformance assessment is possible based on just a single case study like theone reported here.

Response. In the manuscript we included in the discussion section a review of the studies using other classical statistical measures. Now we have put out the word "outperform" and instead we write that our analysis provides an alternative way to describe the spatiotemporal precursory seismicity changes. In the introduction we also state that «Yet, the generalization and reliability of the outcomes of this relatively new approach remains an open question». Indeed more studies are needed and our work contributes exactly to this open question, appearing as promising.

Change.Pag. 8-9, section 5. Discussion

6. On p.3, l.11, I would speak of "hindcasting" rather than "forecasting", since thecorresponding analysis has been made a posteriori after the event occurred.

Response. We agree with the reviewer, we intend to change this as suggested.

Change. Pag.3, Line 11.

7. In order to better understand the meaning of the parameters b and r, please give theGutenberg-Richter relationship explicitly in the text.

Response. Page 3, l. 18 …..where b is the slope of the magnitude-log frequency or G-R relation:

$$\log N = a - bM \quad (1)$$

where N is the cumulative number of events of magnitude equal to or larger than M and a, b are parameters determined by the data.

Change.Pag. 3, Line 20-24.

8. In what sense has the foreshock sequence been produced by a physical process“dominated by a strong chaotic component” (p.3, l.24)?

Response. According to the finding of De Santis et al. (2010) there was a strong chaotic component driven by the accelerated seismic strain release. This is a result of De Santis et al. (2010), not ours. Maybe this is not clearly said. We will write it in a clear manner in the revised text.

Change.Pag. 3, Line 28-30.

9. On p.4, ll.25-28, the symbols Na etc. are used to denote event indices, but ratherresemble window sizes. Using different symbols might help avoiding possible confusionwith standard notions of other papers.

Response.We decided to delete this sentence as it does not add extra information. The procedure of the sliding window is already described just before that.

Change.Pag. 5,Lines 5-7.

10. The motivation for the selection of ACC and small-world index is not clear. Insteadof the small-world index (which should be accompanied by the original reference), itwould make more sense to study ACC and APL, since both are independent whileACC and small-world index are not.

Response.The small-world index is an important statistical measure that reveals how a network structure deviates from random ones that account for regular seismicity. Thus, it can be used to characterize phase transitions that mark the onset of relatively big changes in the underlying topology. The original definition comes from Humphries et al. 2006 and gives an efficient way of characterizing all together the structure of the network with respect to the relation between clustering coefficient and path length.

Change. Pag. 5, Lines 18-21.

11. The statement that the network properties are obtained “by averaging the corresponding properties over all the nodes of the network” (p.5, l.1) is not quite obvious forthe small-world index.

Response.This statement is not for the small-world index but for the path lengths and clustering. We will clarify this in the revised version of the manuscript.

Change. Pag. 5, Lines 14-18.

12. The term “degree” should be briefly explained at its first appearance in the text.

Network scientists know this term very well, but this is not necessarily the case forseismologists.

Response.We agree with the reviewer. We will define it in the revised version.

Change. Pag. 11, Lines 5-7.

13. The term “random regular graph” (p.5, l.30) does not exist – you have either arandom or a regular graph.

Response.Allows us to say that the term “random regular graph” exists and refers to random graphs with uniform degree (see e.g. https://en.wikipedia.org/wiki/Random_regular_graph). However we agree that it is not a common terminology to the non-expert in the field of complex networks readers. Hencewerefer only to random networks

Change.Pag. 6, Line 15.

14. Can one motivate the idea that “hubs that could serve as potential epicenter locators”(p.6, ll.14-15) from known seismological principles?

Response.p.6 l. 24 ….node related to the mainshock epicenter. This observation along with the drop of the b-value (e.g. Papadopoulos et al., 2010) indicates stress increase close to the mainshock epicenter, thus underlying the physical link between the centralization of the BC distribution and the mainshock nucleation process. The BC of all other nodes do not change their values significantly as we present in the manuscript.

Change. Pag.7, Lines 15-18.

15. The authors state that “the recognition of the seismicity anomaly by topologicalmeasures does not discriminate the seismicity style, i.e., foreshocks, swarms or aftershocks”(p.8, ll.18-19). This is surely correct for the present network

constructionapproach. In turn, other recent types of construction mechanisms have been used fordeclustering earthquake catalogs and, thus, identifying fore- and aftershock sequences

(Jimenez et al., EPJST, 2009). It appears reasonable to add a corresponding comment.

Response.The recognition of the seismicity anomaly by topological measures, however, does not discriminate the seismicity style, i.e. foreshocks, swarms or aftershocks. The foreshock nature of the anomaly was detected only by the a posteriori knowledge that the earthquake sequence concluded with a mainshock. In seismology several branching type models have been used to identify space-time clusters, e.g. the epidemic-type aftershock sequence (ETAS) model (OGATA, 1998). Although it was tested for analyzing clustering features of foreshocks (e.g. ZHUANG and OGATA, 2006) no standard method has been introduced so far for the foreshock recognition beforehand. This is also valid for the several techniques introduced for declustering earthquake catalogues (e.g. Jimenez et al., EPJST, 2009). However, the classic seismicity statistics yields possibilities for such discrimination beforehand thanks to the discriminatory power of the b parameter which drops significantly during foreshocks. The drop of b is not only of statistical but also of geophysical value. Therefore, investigating for an equivalent discriminatory topological measure is a challenge.

Change. Pag. 10, Lines6-10.

16. For the definition of the small-world effect in complex networks, both ACC and APLare commonly taken into account together. What the authors report on p.9, l.17, forthe behavior of APL seems not to fully comply with the common view. I recommendconsulting the seminal work by Watts and Strogatz (Nature, 1998) for details.

Response.The small-world index was first introduced by Humphries et al. 2006 http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1560205/ and we use the same definition as appears in that paper. In line 17 we say that the APL for small world network is of the same order as the equivalent random structure. This is in line with the definition and properties of the APL (see Watts, 1999). http://www.cc.gatech.edu/~mihail/D.8802readings/watts-swp.pdf). Actually pure random graphs exhibit relatively small average-path lengths.

However, indeed this is not so clear we will clarify this issue and cite the appropriate papers.

Change.Appendix

17. It is not clear what the authors mean by “local [network] property” (p.9, l.24). BCis clearly a node property, however, its computation requires global linkage informationon the entire network. In this regard, the term “local property” might be misleading.

Response.We agree that could be misdealing but this is the standard terminology used in the field. We will clarify better in the revised version.

Change. Appendix

18. P.9, ll.24-25: "BC(i) indicates that the i[-th] node acts as a central node influencingmost of the other nodes" – how has this influence to be understood in the context ofthe considered earthquake networks?

Response.It means that this node (patch of land) acts as a hub. This means that the seismicity revolves around this particular point. We will explain better in the revised version.

Change. Appendix

19. In Fig. 2c, an additional horizontal line at b=1 might help visualizing the differences for different time windows as discussed by the authors. In the caption, the right panels of Fig. 2b should be mentioned (even though they only represent a zoom of parts of he right panels).

Response.We will make these changes as suggested.

Change. A new yellow horizontal line at b=1 is added in figure 2c and a comment for the right panel is added to the figure caption

20. The cumulated BC (CBC*) is not clearly defined in the text, and its definition andmeaning are not clear from the text. This aspect needs to be clarified.

Response.We will describe it better in a clear manner in the revised version.

Change. Pag.7, Lines 12-13.

21. I recommend including Fig. S1 in the main text. A supplementary information forjust a single figure does not seem necessary.

Response.We agree and we will include it in the main text.

Change. Figure 8 instead of figure S1 is inserted in the main text

22. Throughout the manuscript, there seem to be numerous (yet minor) languageissues like confusion of singular and plural forms, use of articles, word order, etc.

Careful proofreading is recommended prior to resubmission.

Response.We will correct all these issues.

2nd reviewer

1. **Major point**

As I understand, the network analysis does not take into account the different magnitudes of the foreshocks. This means that it could depend on the chosen minimum magnitude of the dataset (now Mc=1.3). I think this is the weakest point of this kind of analysis. Results from some other different choices should be shown, in order to prove that the choice is not critical.

Response. The selection of the minimum magnitude of the data set was not done ad-hoc. The earthquake catalogue was tested for data completeness on the basis of the G-R diagram as done in the classical statistics.

This is an important task as mishandling data may subsequently lead to wrong evaluations for a series of important features, such as seismic rate changes, with implications for the identification of earthquake sequences, e.g. aftershocks.

Indeed the above is not highlighted enough in the text. We will explain it better in the revised version.

Change. Pag.4, Lines 1-3.

2. **Secondary points**

- I suppose the selection of the seismic events is limited by the depth so considering only shallow earthquakes, but this is not said. Could you please specify it? And, how much critical is the choice (e.g. showing results for two other depth choices)?

Response. We have considered the earthquake catalogue of the area without threshold in the focal depth.

However, the majority (nearly 97%) of the events have focal depth less than 30 km, which means that they are shallow.

The remaining may have depth up to about 45 km but we did not remove them from the catalogue allowing for some error to be involved in the depth determination. As a consequence, the data set that we used practically represents the shallow seismogenic layer.

We will write it explicitly in the revised version.

Change. Pag.4, Lines 5-9.

- I believe that some passages of the manuscript would be strengthen by adding some proper references that are now missing. I can suggest some (but the Authors can add alternatives), as the following: Pag.2 line 8. After "(e.g. Bufe and Varnes, 1993)" I would add the sentence: "A recent revision of the method has been proposed in order to cope with some previous limitations (De Santis et al., 2015)."

Pag.3 line 14. I would add at the end of the present sentence the following: "However, around a year before the mainshock possible effects due to fluid migration was found from magnetic data analyses (Cianchini et al., 2012)."

Response.We agree and we will add the appropriate references in the revised manuscript.

Change. Pag.2, Line 9-10& Pag.3 Line 14-15.

- Pag. 7 line 23. After "its occurrence" I would insert the following: "(look also De Santis et al. 2015)".

Response.We agree. We will make the necessary change as suggested.

Change. Pag. 9, Line 7.

- Pag.8 line 1. Please, after "2010" insert: "; De Santis et al., 2011".

Response.We agree and we will do so.

Change. Pag.9, Line 19.

- Fig.2 caption, pag. 16 line 13. When you write "2σconfidence intervals" do you really mean

"±2σconfidence intervals" or "±σ confidence intervals"? Please clarify.

Response.We mean "±2σ confidence intervals. We will clarify this in the revised version.

Change. Caption of figure 2

- Fig. 5 pag. 19 and Fig. 6 pag. 20. Although you already provide the spatial distribution of the earthquakes in Fig. 1, I believe that these Figures would be clearer if associated with the progressive spatial distribution of earthquakes in each frame, even provided in a separate Figure (if the points decrease clarity in reading).

Response.We have now added a new figure (Figure 9) illustrating snapshots of the seismic networks overlaid on the BC measure.

Change. Please see new Figure 9.

Minor points

Response.We agree and we will fix all of them in the revised version.

Change. Done

References

Response.We will add the suggested references

Change. Done

Cianchini G., A. De Santis, D. R. Barraclough, L. X. Wu, and K. Qin, 2012. Magnetic transfer function entropy and the 2009 Mw = 6.3 L'Aquila earthquake (Central Italy), Nonlin. Processes Geophys., 19, pp. 401-409, doi:10.5194/npg-19-401-2012.

De Santis A., Cianchini G., Di Giovambattista, 2015. Accelerating moment release revisited: examples of application to Italian seismic sequences, Tectonophysics, 639, 82-98, 10.1016/j.tecto.2014.11.015.

Foreshocks and Short-Term Hazard Assessment to Large Earthquakes using Complex Networks: the Case of the 2009 L'Aquila Earthquake

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Abstract. The monitoring of statistical network properties could be useful for the short-term hazard assessment of the occurrence of mainshocks in the presence of foreshocks. Using successive connections between events acquired from the earthquake catalogue of INGV for the case of the L'Aquila (Italy) mainshock ($M_w = 6.3$) of 6th April 2009, we provide evidence that network measures, both global (~~e.g.~~ average clustering coefficient, small-world index) and local (betweenness centrality) ones, could potentially be exploited for forecasting purposes both in time and space. Our results reveal statistically significant increases of the topological measures and a nucleation of the betweenness centrality around the location of the epicenter about two months before the mainshock. The results of the analysis are robust even when considering either large or off-centered the main event space-windows.

1 Introduction

Seismicity is a 3-D complex process evolving in the heterogeneous space, time and size domains. Since the birth of the science of seismology about 130 years ago, the underlying statistical properties of seismicity have attracted increasingly great interest (see e.g. a review in Utsu, 2002), enhancing our understanding of the complex physical mechanisms that cause earthquakes. Over the years, several models have been proposed for the description of seismicity. For example, the random walk model (Lomnitz, 1974) was introduced to describe on-clustered background seismicity. However, space-time earthquake clusters deviate significantly from randomness. In fact, the pioneering work of Omori (1894), extended later by others (e.g. Utsu, 1962a, b, Utsu et al., 1995) revealed the strong clustered nature of aftershock sequences following large mainshocks. Aftershocks decay with time in a power-law mode, the so-called Omori law. However, as the decay of aftershocks very often deviates from the simple power-law, the statistical model of Epidemic Type Aftershock Sequences (ETAS) was introduced (Ogata, 1998) to describe the complex pattern of aftershocks time distribution (Zhuang, 2012). On the other hand, a physical approach based on the rate- and state-model of fault friction was also introduced (Dieterich, 1994).

In some occasions, short-term foreshocks preceding mainshocksby hours, days or up to a few months were reported. It was found that the number of foreshocks generally increases with the inverse of time (Mogi, 1962, 1963a, b; Papazachos, 1975; KaganandKnopoff, 1978; Jones and Molnar, 1979; Hainzlet al., 1999; Main, 2000; Papadopoulos et al., 2010). Therefore, foreshocks may provide time-dependent information which may lead to a more robust estimation of the probability for the occurrence of future strong mainshocks(e.g. Agnew and Jones, 1991). However, some mainshocks are preceded by foreshocks while others do not. Long-term accelerating foreshock activity has been also described (for a thorough review see in Mignan, 2011). A very early case in the Hellenic Arc was studied by Papadopoulos (1988), while models for the long-term accelerating seismicity were further developed by others (e.g. BufeandVarnes, 1993).A recent revision of these models has been proposed in order to cope with some previous limitations (De Santis et al., 2015). Another major type of space-time seismicity clusters, termed earthquake swarm, is characterized by a gradual rise and fall in seismic moment release but it is lacking a foreshocks-mainshock-aftershocks pattern (e.g. Yamashita, 1998; Hainzl, 2004;Hauksson et al., 2013). Although seismic swarms are abundant in volcanic and geothermal fields as well as in areas of induced seismicity, caused by fluid-injection, mining or gas recovery, they are not unusual in purely tectonic settings.

Over the last years, the complex network theory has provided a new insight and perspective in analyzing seismicity patterns (Abe and Suzuki, 2004, 2007; Baiesi and Paczuski, 2004, 2005; Barrat et al., 2008; Daskalaki et al., 2014). This line of research is motivated by the concept of self-organized criticality (Bak, 1996) which models structural phase transitions from random to scale-free spatial correlations between seismic events (e.g. Sammis and Sornette, 2002). Yet, the generalization and reliability of the outcomes of this relatively new approach remains an open question.

In this paper, we exploited the tools of complex network theory to identify potential spatio-temporal foreshock patterns that could add value to the short-term earthquake forecasting or hazard assessment. We focused on the case of the shallow, strong ($M_w = 6.3$), lethal mainshock which ruptured the Abruzzo area, central Italy, on April 6th, 2009, at UTC 01:32:39, with an epicenter situated at 42.42°N, 13.39°E (Fig.1), near the city of L'Aquila(http://terremoti.ingv.it/it/). Fault-plane solutions for the mainshock and aftershocks are consistent with predominantly normal faulting striking NW-SE and dipping to SW, with a minor right-lateral component (e.g. Walters et al., 2009).The mainshock was followed by abundant aftershocks with the major events occurring on the7th of April ($M_w = 5.6$) and on the 9th of April ($M_w = 5.4$).Immediately following the mainshock, Marzocchiand Lombardi (2009) began producing daily aftershock forecasts based on a stochastic model that combines the G-R (Gutenberg and Richter, 1944) distribution and space-time power-law decay of triggered shocks.

We selected to study the L' Aquila seismic sequence since themainshock was preceded by abundant foreshocks (Papadopoulos et al., 2010; De Santis et al., 2011), thus allowing to test topological metrics, which are in use in the complex network theory. Such metrics are potential tools for the investigation of short-term precursory seismicity patterns. The aim is to show if and how the exploitation of network theory metrics can independently add value to short-term seismic hazard assessmentin the presence of foreshocks Therefore, before the implementation of selectedtopological metrics, in Section 2 we examined further the seismicity patterns that preceded the L' Aquila mainshock by mainly focusing in statistics of the foreshock sequence in space, time and size (magnitude) domains.

Here, we adopted the term seismic hazard assessment referring to "forecasting"/ "hindcasting"(Evison, 1999; Bormann, 2011), i.e. a warning that a mainshock would probably happen within a specific region in short-term, instead of the term "prediction" which contains a much stronger statement that a mainshock will deterministically happen. In this sense, earthquake forecasts are prospective probabilistic statements specifying the likelihood that target events will occur in space-time subdomains. In a time-dependent forecast, the probabilities $P(t)$ depend on the information $I(t)$ available at time$t$ when the forecast is made (Jordan et al., 2011). A thorough global review has shown that strategies of time-dependent hazard assessments for the earthquake forecasting could be established in a real-time framework (Jordan et al., 2011).

2 Seismicity patterns preceding the L'Aquila mainshock

Long-term seismicity analysis showed that the L'Aquila mainshock was preceded by seismic quiescence prevailing for about 40-50 years, thus very likely filled in a seismic gap (Barani and Eva, 2011). It was also suggested that the earthquake was hindcastedforecasted from a fault-based earthquake rupture model (Peruzza et al., 2011). During the two years before the event, no anomalous strainmeter signal larger than a few tens of nanostrains was visible but during the last few days, there was evidence of dilatancy of saturated rock over the earthquake causative fault, perhaps related to the presence of foreshocks (Amoruso and Crescentini, 2010). However, around a year before the mainshock possible effects due to fluid migration was found from magnetic data analyses (Cianchini et al., 2012).

In the short-term, the mainshock was preceded by a foreshock sequence which developed in two main stages (Papadopoulos et al., 2010). Namely, a posteriori analysis of the INGV catalogue data (http://bollettinosismico.rm.ingv.it) showed that from the beginning of 2006 up to the end of October 2008 the activity was relatively stable and remained in the state of background seismicity (seismicity rate r=1.14, b=1.09; where b is the slope of the magnitude-log frequency or G-R relation). In the earthquake magnitude domain, the magnitude-frequency (or G-R) relation (Gutenberg and Richter 1944) reads as$logN = a - bM$. This relation, whichdescribes the power-law decrease of the number of events with the increase of magnitude, has been found to apply in both clustered and non-clustered types of seismicity (see review in Utsu 2002);*N* is the cumulative number of events of magnitude equal to or larger than *M* and *a*, *b* are parameters determined by the data. By the end of October 2008 up to 26 March 2009, r increased significantly to 2.52 indicating weak foreshock sequence; the b-value did not changed significantly. The weak foreshock sequence was spatially distributed within the entire rupture area determined by the aftershock spatial distribution (Papadopoulos et al. 2010, and their Fig. 1c). In the last 10 days before the mainshock, strong foreshock signal became evident in space with dense epicenter concentration in the hanging-wall of the Paganica fault (Fig. 1), in time (r=21.70 events/day) and in size (b=0.68). It has been also suggested by De Santis et.al.,2010, that the foreshock sequence was produced by a physical process dominated by a strong chaotic component as recognized by the accelerated strain release. (De Santis et al., 2011).

We examined further the seismicity evolution in the time-space-size domains before the L' Aquila mainshock as illustrated in Fig. 2. The earthquake catalogue of INGV (http://legacy.ingv.it/roma/reti/rms/bollettino/index.php?lang=en) was implemented in our seismicity analysis with data covering the time period from 1st January 2008 to 30th June 2009. The earthquake catalogue was tested for data completeness on the basis of the G-R diagram and the magnitude cut-off Mc=1.3was selected, which is consistent with previous findings (e.g. Papadopoulos et al., 2010).as done in the classical statistics. This is an important task as mishandling data may subsequently lead to wrong evaluations for a series of important features, such as seismic rate changes, with implications for the identification of earthquake sequences, e.g. aftershocks. We have considered the earthquake catalogue of the area without threshold in the focal depth. However, the majority (nearly 97%) of the events have focal depth less than 30 km., which means that they are shallow. The remaining may have depth up to about 45 km but we did not remove them from the catalogue allowing for some error to be involved in the depth determination. As a consequence, the data set that we used practically represents the shallow seismogenic layer.

Figure 2a shows thecumulative number of earthquake events within a circle of radius of 30 km from the L' Aquila mainshockepicenter. The dramatic increase of the seismicity rate in about the last 3 months before the mainshock of 6 April 2009 is evident. Particularly, in the last 10 days the seismicity rate increased at significance level 99% according to the z-test, as it was already shown in a previous paper (Papadopoulos et al., 2010). We tested this pattern for several radii gradually decreased up to 5 km or increased up to 100 km from the mainshockepicenter. It was found that the pattern was still significant at level 95%. However, for radii of less than 5 km or more than 100 km the pattern gradually loosed significance due either to the decreasing number of events involved or to the inclusion of increasing number of events associated with other seismogenic sources.

With the increase of the seismicity rate in the last 10 days, that is during the strong foreshock stage, the mean distance of foreshock epicenters from the mainshockepicenter decreased, being about 7 km (Fig. 2b). The time evolution of the parameter b before (red) and after (blue) the L' Aquila mainshock showed also very distinct patterns (Fig. 2c). Before the foreshock sequence it varied from 0.9 to 1.2, that is it was close to the theoretical value of 1. During the weak foreshock activity b remained also close to 1. About two months before the mainshock it dropped gradually reaching values of less than 0.7 in the last 10 days. We applied the Utsu (1992) test for testing the significance level, p, of the b-value variation. In the last 10 days it was found p=0.002, which means significance level of 0.998 in the b-value drop.

3 Topological metrics

Building up on previous efforts (Abe and Suzuki, 2004, 2007; Baiesi and Paczuski, 2004, 2005; Barrat et al., 2008; Daskalaki et al., 2014), exploiting the arsenal of complex networks, we were able to independently investigate statistically significant changes in the underlying seismic network topology marked about two months before the mainshock. Our analysis was based on the earthquake catalogue of INGV.

We discretized the area under study (Fig. 1) into square cells with a side of 0.1^o. Then, we tessellated the catalogue into successive overlapping sliding windows. For each sliding window, a network was constructed by linking cells successively in time, when seismic activity was observed within cells. Denoting by $t_i, t_{i+1}$the time instances when two successive seismic events occur withini and j cells, respectively, then we linki and j cells$(i \rightarrow j)$, which represent nodes of the underlying network. This approach is based on the Abe and Suzuki (2004, 2007) approach. The use of the sliding window allows the tracing of the temporal changes in the network topology (Daskalaki et al., 2014). Here, we propagated the sliding window using two alternatives: either by a constant-time period (here, one day) or by constant number of seismic events (here set to 10 events). Let N_a, N_b and N'_a, N'_b be the ends of the k-th and $(k+1)$-th windows in the catalogue. Then, $N'_a = N_a + N_{a-day}$ and $N'_b = N_b + N_{b-day}$, where N_{a-day} and N_{b-day} is the number of events in the catalogue until the next time period from N_a and N_b, respectively.

Within each sliding window, we measure study the following properties of the underlying directed networkWithin each sliding window,: the small-world index (SW), the average clustering coefficient (ACC), and the betweenness centrality (BC) and the mean degree of the underlying degree distribution (Newman, 2003; Albert and Barabasi, 2002; Costa et al., 2007; Fagiolo, 2007; see in Appendix for mathematical definitions). Tthe clustering coefficient is the ratio between all directed triangles actually formed by node *i* and the number off all possible triangles that node*i* could form (Fagiolo, 2007) and consequentlyby averaging the *ACC* measures the cliquishness (structure) of the network(Watts and Strogatz, 1998). Note that the BC metric is a property that refers to a certain node in the network, while the *ACC* and the mean degree are global network properties in the sense that they are obtained by averaging the corresponding properties over all the nodes of the network.It is known that nodes exhibiting high values of BC are highly participating to the flow of information, including flow of energy, in the network. The small-world index is an important statistical measure that reveals howa network structure deviates fromrandom structures that account for regular seismicity. Thus, the SWitindex can be used to characterize phase transitions that mark the onset of relatively big changes in the underlying topology. The original definition comes from Humphries et al. (2006) and gives an efficient way of characterizing all together the structure of the network with respect to the relation between clustering coefficient and path length.

In order to detect statistically significant changes between the measures obtained from the emergent seismic networks and the ones resulting from consistent random network realizations, the following procedure was applied. Within each sliding window, we constructed an ensemble of 500 realizations of consistent random networks, i.e. random networks with the same number of nodes and with connectivity probability equal to the average degree (see appendix for definition) of the emerged seismic network divided by the number of nodes (Newman, 2003; Albert and Barabasi, 2002). For each of the 500 random network realizations, we computed the statistical measures mentioned above. We adopted as statistically significant the values that were above the 95% or below the 5% of the distributions calculated from the random networks.

In order to test the robustness of the outcomes of the analysis, we constructed networks using different values of sliding window lengths and shift steps as well as different sizes of centered or off-centered,with respect to the mainshockepicenter (42.42°N, 13.39°E), space-windows. Within a wide range of these values, the outcomes of the analysis were equivalent. As during the two years period before the mainshock, no anomalous strainmeter signal larger than a few tens of nanostrains was visible, it was suggested that the volume of the possible earthquake preparation zone was limited to less than 100 km^3(Amorusoand Crescentini, 2010).This is also valid for the seismogenic zone as determined by the area covered by the

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cloud of foreshocks and aftershocks (Fig. 1). Therefore, the space-windows were selected larger than the seismogenic area of the earthquake sequence, so that we would not miss any critical seismicity information.

4 Results

For our illustrations, we show the results obtained using a sliding window with a shift step of either constant-time of one day or of constant-number-of-events $N_s = 10$ and a space- window centered at the mainshockepicenter with two different radius,$R_1 = 1^o$ and $R_2 = 3^o$. The initial size of the sliding window was set to$N_0 = 100$.~~Off-the-epicenter analysis was also employed resulting to equivalent outcomes. The results obtained with an off-centered space- window are shown inFig.S1 in the supplementary material (see also below).~~The total number of cells were 400 and 3420 for $R_!$and R_2radius, respectively. The resulting time-series of the statistical measures ACC and SW index in the period from 1January 2006 to 30 June 2009usingthe centered at the mainshockepicenter space-window with radius$R_1 = 1^o$ are shown in Fig.3.The time evolution of the network measures indicates the existence of two distinct phases/structures with an apparent in-between phase-transition initiating around two months before the mainshockof 6th April 2009 (Fig. 3). The phase-transition corresponds to the period where the weak stage of the foreshock sequence was developed. The initial phase pertained to the period from the beginning of the catalogue segment examined until about two months before the mainshock, whilethe second phase is associated with the aftershock sequence. In the initial phase, the network resembles a random ~~regular~~ graph whose topology is characterized bythe ACC and SW indices within the statistically significant thresholds set by the random network realizations. In the aftershock period, our analysis revealed a statistically significant change in the emerged network structure. In particular, the averageACCjumps up to higher values around 0.5~~,~~ (and remains high) and the SW index exceeds 10~~6~~ indicating the strong small-world character of the underlying topology.

For larger space-windows of $R_2 = 3^o$ (Fig. 4), the results are, for any practical means, equivalent to the case of $R_1 = 1^o$. Of particular interest are the intermediate intervals between the above two distinct phases of network structures (around two months, and especially 10 days, before the mainshock). In terms of network topology interpretation, higher values of ~~the~~ACC implie~~s a~~ more clustered and organized seismicity pattern. Furthermore,~~theobservation (~~within the period of two months,~~)of~~ the *BC*reveals a~~the~~transition between the two phases, since the spatial distribution of *BC* is localized to few nodes, which act as hubs. This means that the seismicity revolves around this particular point (Fig. 5 and 6). These hubs are the stopover between any two nodes and consequently, the distance between any two nodes is reduced. The seismicity transition which is captured in the network topology transition is also confirmed by the evolution of the SW index: it remains within the expected range of values set by the random configuration until two months before the mainshock; thenit passes the threshold and remains above it for the whole period afterwards until the mainshock, thus marking the secondforeshock phase. In this phase, the emergent topology is characterized by statistically significant more clustered networks, with profound small-world characteristics.It is worthy to mention that the*ACC* measure depends~~ed~~on ~~from~~ the mean degree. Fig. 7 shows the evolution of the mean degreefor thecase of sliding windows with a constant time shift of 1 day. Clearly,the mean degree does not exceed the we don't see any statistical violation fromstatistically significant bounds of 5% and 95% in the underlying seismic network topology.

Yet, an important question that naturally emerges is the following: is it possible to “forecast” the spatial location of a probable large earthquake from the identification of phase changes that have arisen on the topology of the underlying emerged networks? To respond to such acrucial question we computed the $BC$for each node, trying to identify hubs that could serve as potential epicenter locators. Figures5 and 6 show snapshots of the BCmap for the space-window ofR_1 and R_2radii, respectively,around the mainshockepicenter, before (Fig. 5a-h and 6a-h) and after (Fig. 5i and 6i) the mainshock. Interestingly, it is shown that during the period until the 20thof January 2009, the BCvalues appear randomly dispersed in space. However, about two months before the mainshock and in particular from the 30th of January 2009 a different pattern emerged. Specifically, at the cell of the mainshockepicenter, there was a persistent appearance of large values of theBCthroughout the entire period from the end of January 2009 until the occurrence of the mainshock(Fig. 5a-h). This is clearly illustrated in Fig.5j-kdepicting that the cumulativeBC, which is computed atofthe node of the epicenter (i.e. the mainshock cell, (denoted by CBC^*), increases sharply and monotonically, approximately two months before the date of the mainshock, without any intermediate plateaus. Thus, there was a centralization of theBCdistribution at the cell of the epicenter. This behavior is unique and characteristic just for the node related to the mainshockepicenter. This observation along with the drop of the b-value (e.g. Papadopoulos et al., 2010) indicates a stress increase close to the mainshockepicenter, thus underlying the physical link between the centralization of the BC distribution and the mainshock nucleation process. The BC of all other nodes do not change their values significantly as we presented here. The BCs of all other nodes of the network reach plateaus, i.e. their (cumulative) changes during the two-month period before the main event is negligible compared to the CBC^*. The corresponding CBC^*continues to increase after the main event until late June, a behavior which is related to the aftershock activity.The above pattern characterizes both areas determined by radii$R_1$and R_2.

In order to test if these results were sensitive to the selection of the center of the space-window used for the construction of the network, we repeated the analysis using off-the epicenter-centered space-windows. Off-the-epicenter analysis was also employed resulting to equivalent outcomes. In Fig.8S1 in the supplementary material, we depict theBC map for the space-window with radius R_1centered at the point 42.42°N, 13.39°E, which is about 80 km south from the mainshock epicenter. As it is shown, the results are qualitatively equivalent with those of Fig.5 and 6, i.e. with the results obtained when using a space-window centered at the epicenter of the mainshock. Finally in Fig.9 we illustrate snapshots of seismic networks overlaid on the BC contours for the periods: (a) 26 September to 10 October 2008, (b) 14 to 27 January 2009, (c) 20 March to 4 April 2009, and, (d) 1 to 16 April 2009.

Off the epicenter analysis was also employed resulting to equivalent outcomes. The results obtained with an off-centered space- window are shown inFig.8S1 in the supplementary material (see also below).

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5 Discussion

The drastic increase of the seismicity rate is a common feature in foreshocks, swarms and aftershocks. Therefore, such seismicity clusters are traditionally considered as retrospective designations: they can only be identified as such after an earthquake sequence has been completed (Jordan et al., 2011) given that certain criteria for the discrimination of foreshocks from other types of space-time seismicity clusters are needed (Ogata, 1998). Although this is in general true, the retrospective analysis of the 2009 L' Aquila foreshock sequence showed that in a scheme of regular, daily statistical seismicity evaluation, the ongoing state of weak foreshock activity would be detectable in about one or two months before the mainshock (Papadopoulos et al., 2010). Then, the strong foreshock signal, being evident in the space, time and size domains could be detectable a few days before the mainshock. The presence of foreshocks, as states of elevated seismicity with respect to background seismicity level, could be also suggested by independent approaches, such as Poisson Hidden Markov Models (Orfanogiannaki et al., 2014). The spatial organizations of foreshocks as a tool to forecast mainshocks has been positively examined (Papadopoulos et al., 2010; Lippiello et al., 2012; see also results in section 2). In the size domain, the drop of the G-R b-value in foreshock sequences (Papadopoulos et al., 2010; see also results in the present paper) is of crucial importance for the real-time recognition of foreshock activities based on seismicity analysis. However, whatever is the method to detect an ongoing foreshock activity, the magnitude of the forthcoming strong earthquake, M_o, would remain uncertain although preliminary results from a set of few but well-determined foreshock sequences around the globe tentatively indicated that M_o is a function of the area covered by the foreshock activity (Papadopoulos et al., 2015).

Sugan et al. (2014) analysed continuous waveforms from 10 broadband seismic stations in a 60 km radius from the epicenter and for approximately 3 months before the mainshock. They found that the relocated foreshocks mostly activated the deepest northern portion of the L'Aquila main fault plane in the 3 months period preceding the $M_w = 6.3$ event. The $M_w = 6.3$, 6 April 2009 L'Aquila earthquake was preceded by a long suite of foreshocks, the largest one of magnitude $M_L = 4.1$ (30thof March at 13:38 (UTC)) marked the beginning of an abrupt temporal change in different seismic parameters, such as the b value [Papadopoulos et al., 2010; Sugan et al., 2014], the spatiotemporal distribution of the events [Telesca, 2010]and the P-to-S wave velocity ratio [Di Luccio et al., 2010; Lucente et al., 2010]. Calderoni et al. (2014)state that before that event, seismicity was concentrated to the north of the volume where the main shock nucleated. After the $M_L = 4.1$ event, rate and magnitude of foreshocks increased and seismicity migrated toward the main shock nucleation zone. Gulia et al. (2016)studied a circular area of 20 km radius,centered on the mainshockepicenter. They observed a foreshock sequence started three months beforethe mainshock, activating a region of about 10 kmlength.

Compared to the above studies our analysis provides an alternative way to describe the spatiotemporal precursory seismicity changes. Thus, it is worth to mention that our method succeeded to determine the mark of onset of significant changes in seisimicity when also considering an off-epicentered analysis (Fig.8). Based on the BC measure, the identification of the spatial location of the epicenter two months before the main event was also possible.

One of the advantages of the complex network theory is that networks may be used to identify efficiently, within the nonlinear dynamics theory framework, phase-transitions that mark the onset of big changes in the underlying seismicity.The wealth of statistical measures of the reconstructed network activity (such as the small-worldness, path-length, local and global clustering coefficient, betweenness centrality) offers many different views and tools for characterizing the underlying varying topology.In this paper, w We showed that key topological measures of the emerged seismic network constitute an independent tool for hazard assessment of the occurrence of the mainshock in the short-run. Such topological measures perform at least equivalently to classic statistics as regards the evolution of the earthquake sequence in space and time. In this sense, the proposed approach looks promising as it could identify (retrospectively as all other methods until now) quite efficiently, about two months before the mainshock, the location of the mainshockepicenter. Interestingly, in the a posteriori analysis of the 2009 L' Aquila seismic sequence, the betweeness centrality and its cumulative expression, which are local statistical network measures, started to pinpoint the nucleation area of the forthcoming strong earthquake two months before its occurrence (Fig. 9) (look also De Santis et al. 2015). In this sense, the topological measures appear to outperform other observables reported in previous statistical works in terms of the detection of the onset of "persistent" steep changes in the system's observables.

Nevertheless, the detection of a seismicity anomaly in space and time by topological measures does not provide evidence on the seismicity style beforehand: it is designated only retrospectively. In fact, the foreshock style of seismicity becomes obvious only with the a posteriori knowledge that the anomaly concluded with a strong mainshock. Such knowledge, however, could be obtained from classic statistics beforehand on the basis of the 3-D space-time-size seismicity analysis.Furthermore, Tthe role of the parameter b variations is critical. Strong variations of b across different stress regimes imply that this parameter acts as a stress meter that depends inversely on differential stress (e.g. Schorlemmer et al., 2005; Narteau et al., 2009 and references therein). Observations on seismic sequences have shown that b usually drops and becomes significantly lower in foreshocks than in aftershocks or in background seismicity (Papazachos ,1975; Jones and Molnar, 1979; Main et al., 1989; Molchan et al., 1999; Enescu et al,. 2001; Nanjo et al., 2012). This was also the case of L'Aquila (Papadopoulos et al., 2010; De Santis et al., 2011). Recently, Olami-Feder-Christensen (OFC) spring-block models and simulation experiments were utilized to bridge the macroscopic b-value to source mechanics, e.g. to elastic properties, as well as to stochastic structural heterogeneities in the source, thus modeling significant changes ofb, e.g. during foreshocks, with a process of material softening (Avlonitis and Papadopoulos, 2014).

Hence, in view of the statistical and geophysical significance ofb, it becomes interesting to investigate for alternative metrics, such as the topologicalones that the network theory provides, which may outperform classic statistics in terms of spatio-temporal forecasting.

6 Conclusions

Utilizing complex network theory, we showed that key topological measures, such as the average clustering coefficient (ACC), small world index (SW) and the betweenness centrality (BC), could serve as potential indices for the short-term seismic hazard assessment. Of particular interest is the detection of forthcoming mainshocks in the presence of foreshocks.

In the case of foreshocks that preceded the L'Aquila (Italy) mainshock ($M_w = 6.3$) of 6th April 2009, statistically significant changes of the network topology as reflected by certain global measures, such as the SW index and ACC, emanated simultaneously about two months before the mainshock. In this sense, the topological measures perform equivalently to classic statistics. However, a clear centralization of the BCaround the location of the mainshockepicenter appeared again about two months before the mainshock, persisting up to the mainshockoccurrence~~. From this point of view one may recognize that the BCoutperformed the classic space-time seismicity statistics.~~

The recognition of the seismicity anomaly by topological measures, however, does not discriminate the seismicity style, i.e. foreshocks, swarms or aftershocks. The foreshock nature of the anomaly was detected only by the a posteriori knowledge that the earthquake sequence concluded with a mainshock. In seismology several branching type models have been used to identify space-time clusters, e.g. the epidemic-type aftershock sequence (ETAS) model (OGATA, 1998). Although it was tested for analyzing clustering features of foreshocks (e.g. ZHUANG and OGATA, 2006) no standard method has been introduced so far for the foreshock recognition beforehand. This is also valid for the several techniques introduced for declustering earthquake catalogues (e.g. Jimenez et al., EPJST, 2009). However, ~~T~~the classic seismicity statistics yields possibilities for such discrimination beforehand thanks to the discriminatory power of the b parameter which drops significantly during foreshocks. The drop of b is not only of statistical but also of geophysical value. Investigating for an equivalent discriminatory topological measure is a challenge.

The proposed approach holds promising regarding the identification of spatio-temporal patterns related to the underlying seismicity and thus could be potentially serve as alternative and/or complementary to well-established traditional statistical methods for short-term, time-dependent hazard assessment of earthquakes.

Appendix

Within each sliding window, we computed the following statistical properties of the emerged networks (Watts and Strogatz, 1998; Newman 2003; Albert and Barabasi 2002; Costa et al. 2007, Fagiolo, 2007):

a) The mean d~~D~~egree.~~-~~G~~g~~enerally thedegree of a node $i$is the number of edges connected to a node(Newman, 2003). In directed networks a node has both an in-degree and an out-degree, which are the numbers of in-coming and out-going edges respectively (Newman, 2003).Averaging over all the nodes of the network we get the mean degree.

~~Within each sliding window, we computed the following statistical properties of the emerged networks (Watts and Strogatz, 1998; Newman 2003; Albert and Barabasi 2002; Costa et al. 2007):~~

b) The average clustering coefficient (ACC), which reflects the average, the prevalence of clustered connectivity around individual nodes. The $ACC$is defined as the mean value of all clustering coefficients c_i:

$c_i = \frac{(A+A^T)^3_{ii}}{2[k_{tot}(k_{tot}-1)-2(A^2)_{ii}]}$.

$A$is the adjacency matrix of the network, k_{tot} is the summation of inward and outward degrees, i.e. $k_{tot} = k_{in} + k_{out}$ and the parenthesis $()_{ii}$ indicates the main diagonal.The$c_i$is the ratio between all directed triangles actually formed by node i and the number off all possible triangles that node$i$ could form (Fagiolo, 2007)~~and consequently by averaging the ACC measures the cliquishness (structure) of the network(Watts and Strogatz, 1998)~~. It is a natural extension of the Watts and Strogatz definition, since if it restrictedto the undirected networks gives the same results.

The ACCranges from zero to one. Small values of ACC of order $ACC = \frac{\bar{k}}{N}$ correspond to random network structures (encounter in normal seismicity periods).

c) The small-world index(SW)defined as:

$SW = \frac{ACC_{rel}}{APL_{rel}}$.

$ACC_{rel} = \frac{ACC}{ACC_{rand}}andACC_{rand}$ is the average ACC computed from an ensemble of 1000 random network realizations (with the same number of nodes N and same mean $k_{tot}(i)$). APL_{rel}stands for the relative average path length defined as:$APL_{rel} = \frac{APL}{APL_{rand}}$, where$APL$ is the average path length of the underlying seismic network defined by: $APL = \frac{\sum d_{i\to j}}{N(N-1)}$.

$d_{i\to j}$is the shortest path between nodes i and $j$and APL_{rand} is the average path length computed from the ensemble of 1000 equivalent random networks. Small-world networks are formally defined as networks that are significantly more clustered than random networks, yet have approximately the same characteristic path length as random networks. In the small-world topology $ACC \gg ACC_{rand}$ and $APL_{rand} \approx APL \rightarrow SW \gg 1$, meaning that high (abrupt) increment of SW indicates the transition from normal to abnormal seismicity as it is reflected to network topology.

d) The betweenness centrality (BC) defined as the fraction of all shortest paths in the network that pass through a given node. Bridging nodes that connect disparate parts of the network often have a high betweenness centrality. The betweenness centrality of a node i is defined as:

$$BC(i) = \sum_{j \neq i \neq k} \frac{g_{jk}(i)}{g_{jk}}.$$

$g_{jk}(i)$ is the number of shortest path passing from node i, and g_{jk} is the number of shortest paths between nodes i and j. Note that the betweenness centrality is a local property of the network. Higher values of $BC(i)$ indicates that the i node acts as a central node influencing most of the other nodes in network. This means that this node (patch of spaceland) acts as a hub.

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Figures

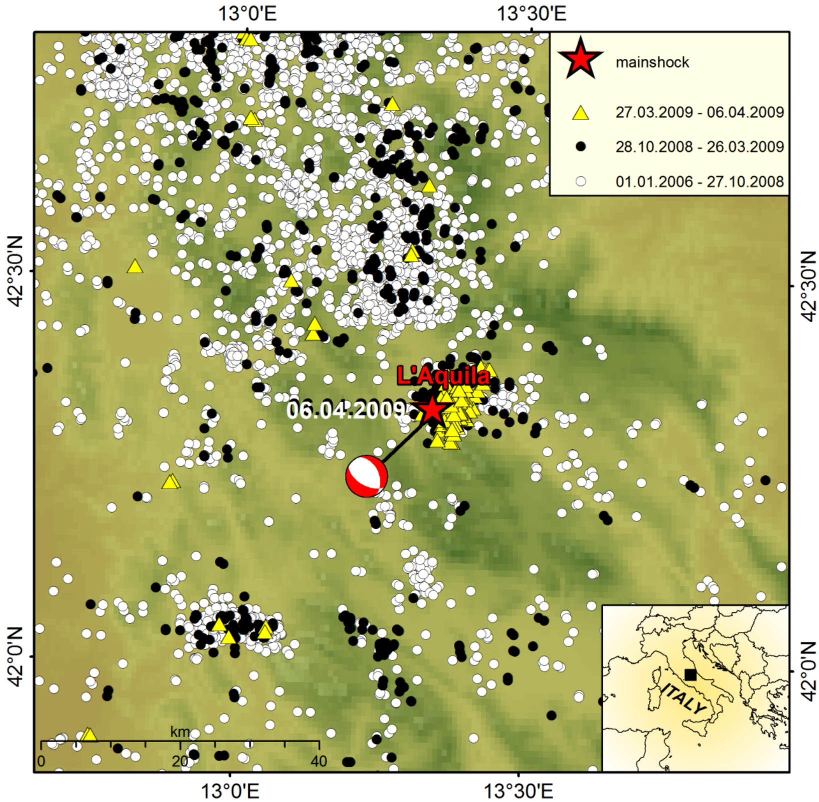
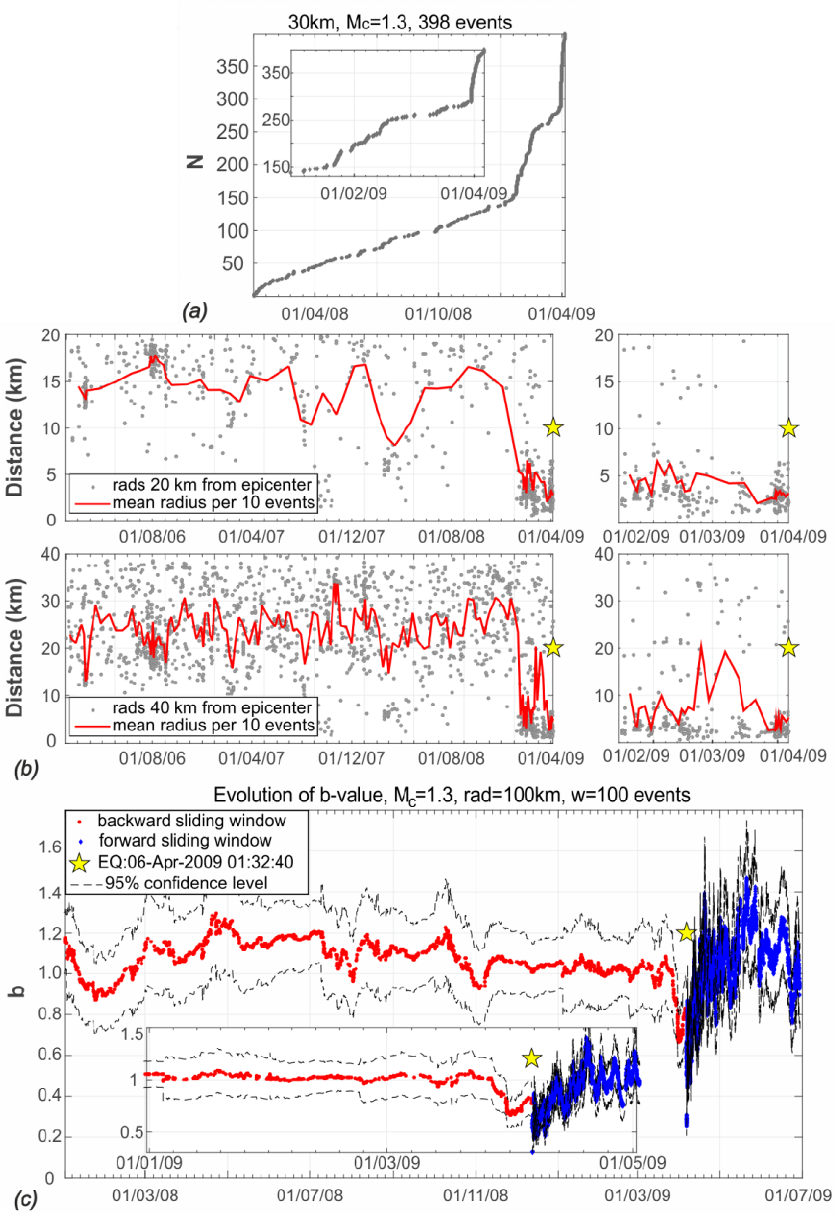


Figure 1. Epicentral distribution of earthquakes in the area of L'Aquila for the time interval extending from 01.01.2006 to 30.06.2009.The focal mechanism of the L' Aquila mainshock (star) was calculated by INGV. Note the dense concentration of foreshock epicenters close to the mainshockepicenter in the last 10 days preceding the mainshock occurrence, which indicates that foreshocks moved towards the mainshock nucleation area.


30km, Mc=1.3, 398 events
N
(a)
01/04/08
01/10/08
01/04/09
01/02/09
rads 20 km from epicenter
mean radius per 10 events
rads 40 km from epicenter
Distance (km)
01/08/06
01/04/07
01/12/07
01/08/08
01/03/09
(b)
Evolution of b-value, Mc=1.3, rad=100km, w=100 events
backward sliding window
forward sliding window
EQ:06-Apr-2009 01:32:40
95% confidence level
b
01/01/09
01/05/09
01/03/08
01/07/08
01/11/08
01/07/09
(c)

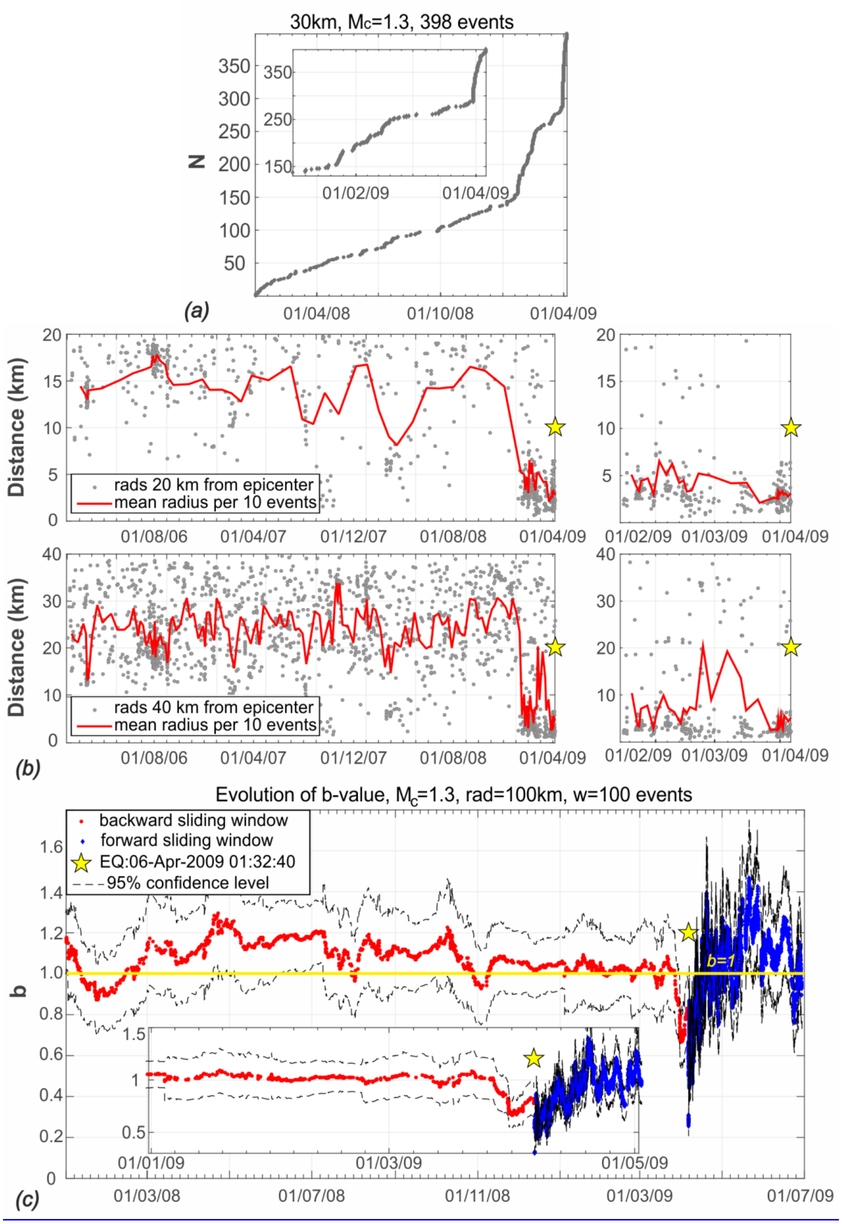

30km, Mc=1.3, 398 events
N
01/02/09
01/04/09
01/04/08
01/10/08
01/04/09
(a)
Distance (km)
rads 20 km from epicenter
mean radius per 10 events
rads 40 km from epicenter
mean radius per 10 events
01/08/06
01/04/07
01/12/07
01/08/08
01/04/09
01/02/09
01/03/09
01/04/09
(b)
Evolution of b-value, Mc=1.3, rad=100km, w=100 events
backward sliding window
forward sliding window
EQ:06-Apr-2009 01:32:40
95% confidence level
b
b=1
01/01/09
01/03/09
01/05/09
01/03/08
01/07/08
01/11/08
01/03/09
01/07/09
(c)

Figure 2. Time-space-size evolution of the L' Aquila foreshock sequence based on the INGV earthquake catalogue. (a) Cumulative number of earthquake events within a circle of radius of 30 km from the mainshockepicenter. The dramatic increase of the seismicity rate in about the last 3 months and particularly in the last 10 days (significance level 99%) before the mainshock of 6 April 2009 is evident. (b) Time evolution of the mean distance (red line) of foreshock epicenters from the mainshockepicenter (yellow star) for radius of 40 km (upper panel) and 20 km (lower panel). Calculation has been made for sequential but not overlapping sets of 10 events. Yellow star indicates the mainshock origin time. The mean distance gradually decreased being minimal in the last 10 days, that is during the strong foreshock stage. The right panels of the figure represent a zoomed area of the left onesshowing thetime evolution of the mean distance of foreshock epicenters from the mainshockepicenterfor the last 2 months(c) Time evolution of the parameter b calculated backwards before the L' Aquila mainshock (red) and forwards after the mainshock (blue). The parameter b was calculated for sequential segments of the catalogue with a constant number of n=100 events and step of 1 event under the condition that the magnitude range in each segment was at least 1.4 as suggested by Papazachos (1974). The aim was to achieve stability in the results. If this condition was not satisfied then n was increased gradually with step of 1 event until the condition was satisfied. Black lines represent ±2σ confidence intervals. Yellow star as in Fig. 2b. The parameter b dropped gradually and reached values less than 0.70 in the last 10 days before the mainshock. In the aftershock period the b-value increased rapidly above 1. Yellow line in b=1makes the differences for different time windows more obvious..

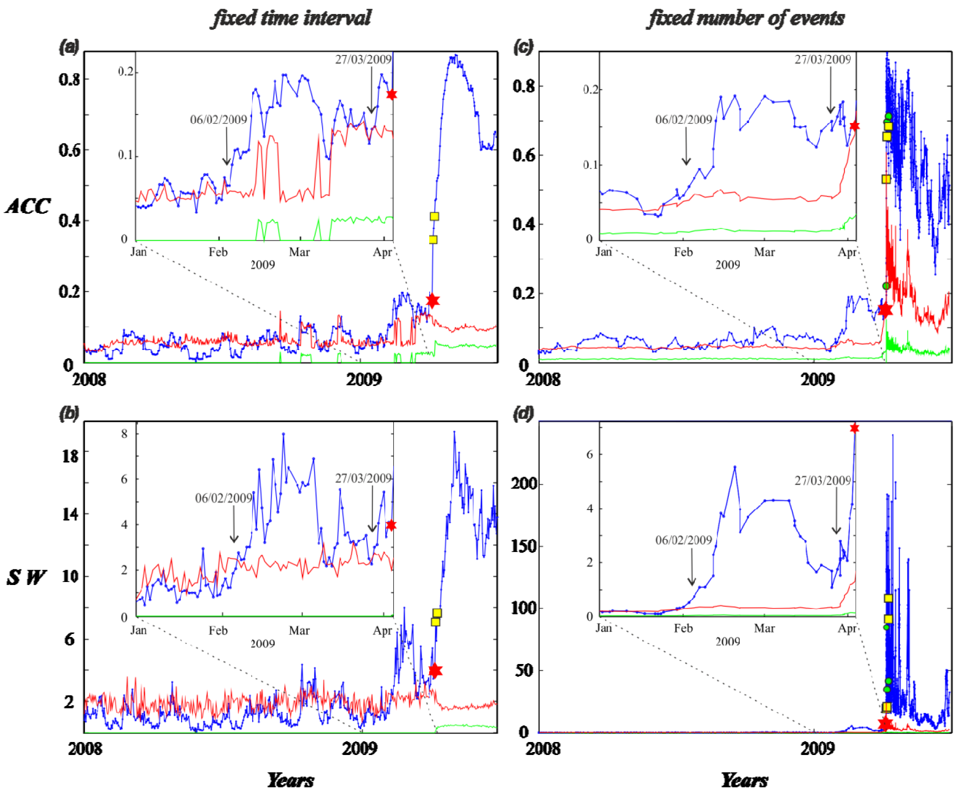


Figure 3. ACC and SW indices global statistical network measures from 01.01.2008 to 30.06.2009. Computations were performed in the space-window centered at the mainshock epicenter (42.42°N, 13.39°E), with radius $R_1 = 1^o$. Left column depicts the results obtained with a constant time shift of 1 day. Right column depicts the results obtained with a constant number of events shift. Earthquakes in the magnitude ranges of $4.3 \leq M \leq 4.9$ and $5.0 \leq M \leq 5.6$ are marked with green circles and yellow squares, respectively. The mainshock that occurred on April 6th, 2009 is marked with a red star. Red and green lines represent statistically significant levels of 95% and 5%, respectively (see description in the methods section).The inset shows a zoom in the period January 1-April 6, 2009. The arrow in the inset marks the onset of the statistically significant changes from the random network topology.

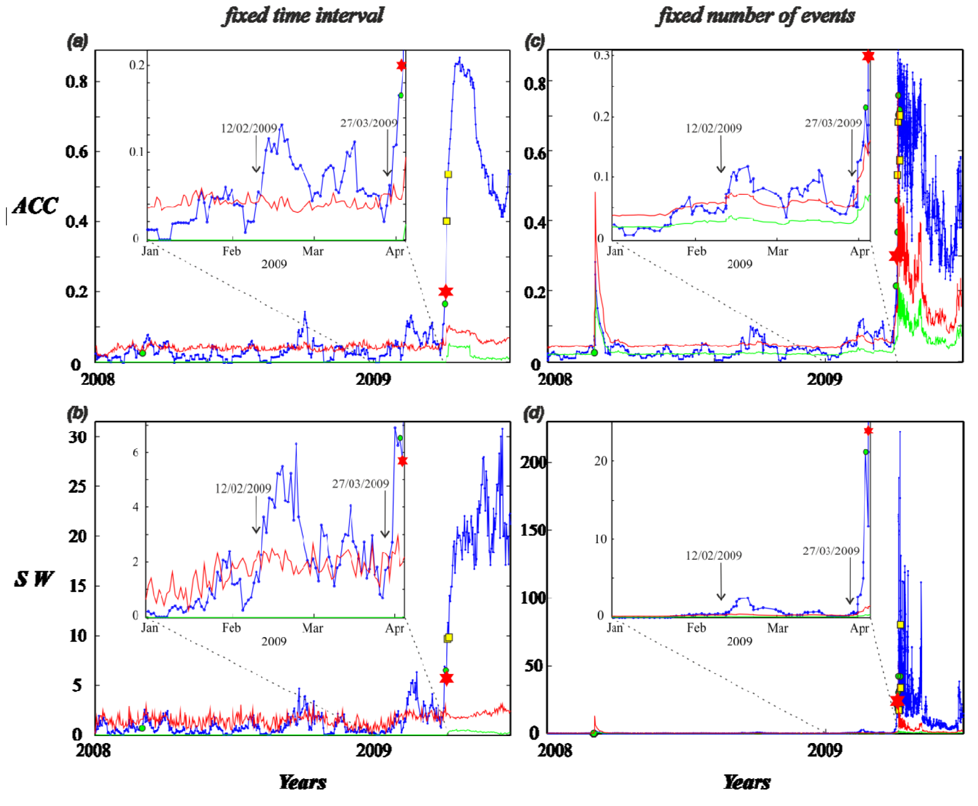


Figure 4. As in Fig. 3 for computations performed with radius $R_2 = 3^o$.

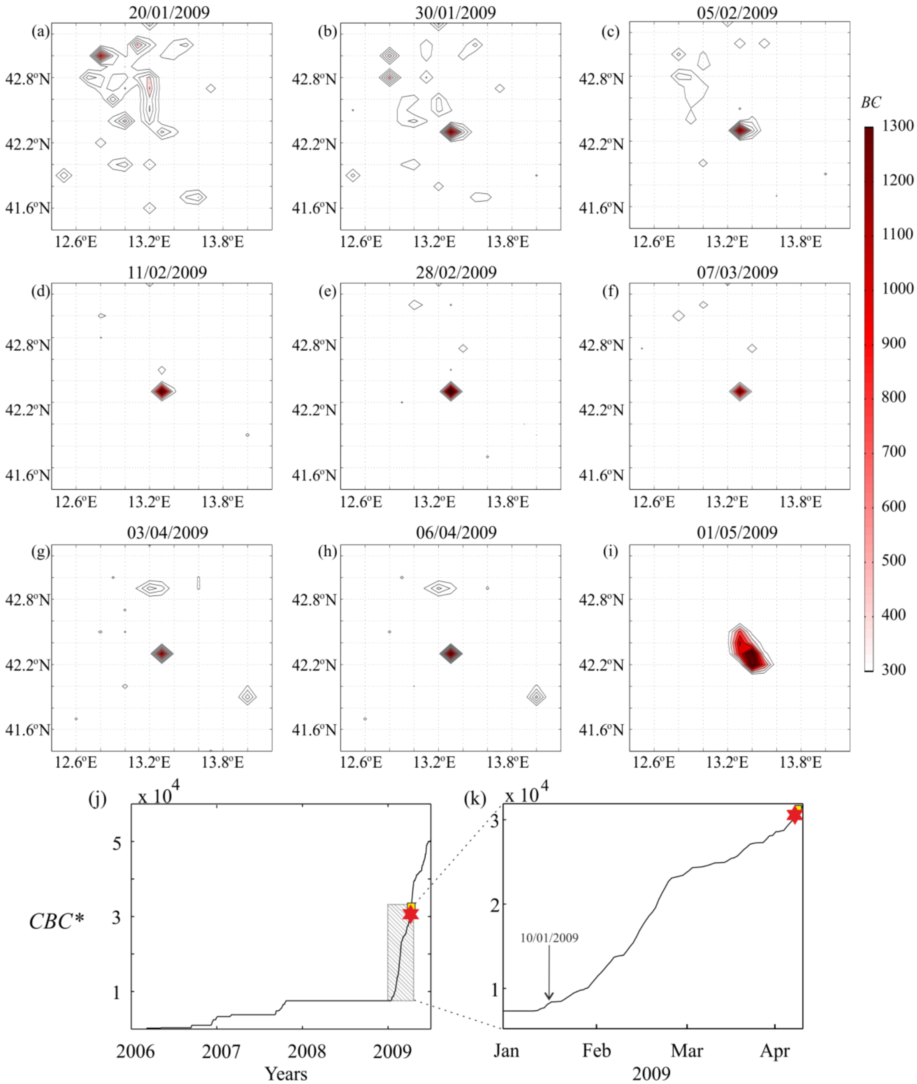


Figure 5. Betweeness cCentrality (BC) computations in the space-window centered at the mainshockepicenter (42.42°N, 13.39°E) with radius$R_1 = 1^o$: (a-i) snapshots of the BC maps for each cell from 20.01.2009 to 01.05.2009; (j, k) cumulative BC computed at the mainshock cell (CBC^*) from 01.01.2006 to 30.06.2009 (j), and from 01.01.2009 to 06.04.2009 (k). The mainshock occurred on April 6th, 2009 (red star).

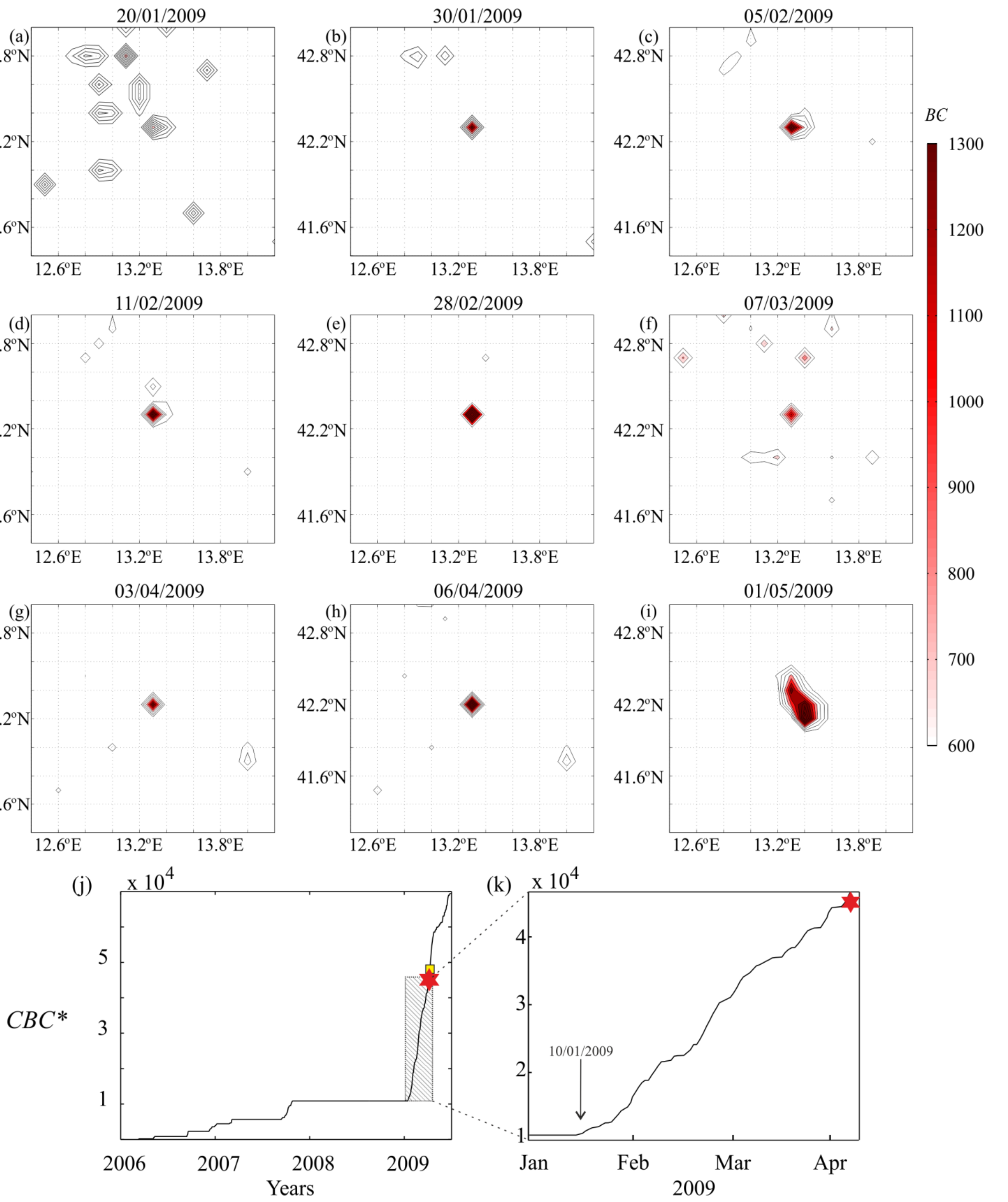


Figure 6. As in Fig. 5 for space-window with radius$R_2 = 3^o$.

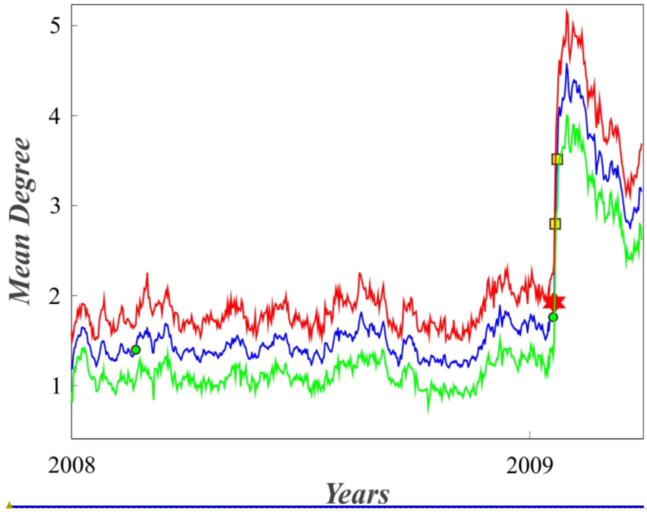


Figure 7. The mean degree of the seismic networks (blue line) as computed using sliding windows with the constant time shift of 1 day. Red and green lines represent statistically significant levels of 95% and 5%, repsectively, as obtained from an ensemble of equivalent random networks, (see description in the methods section).

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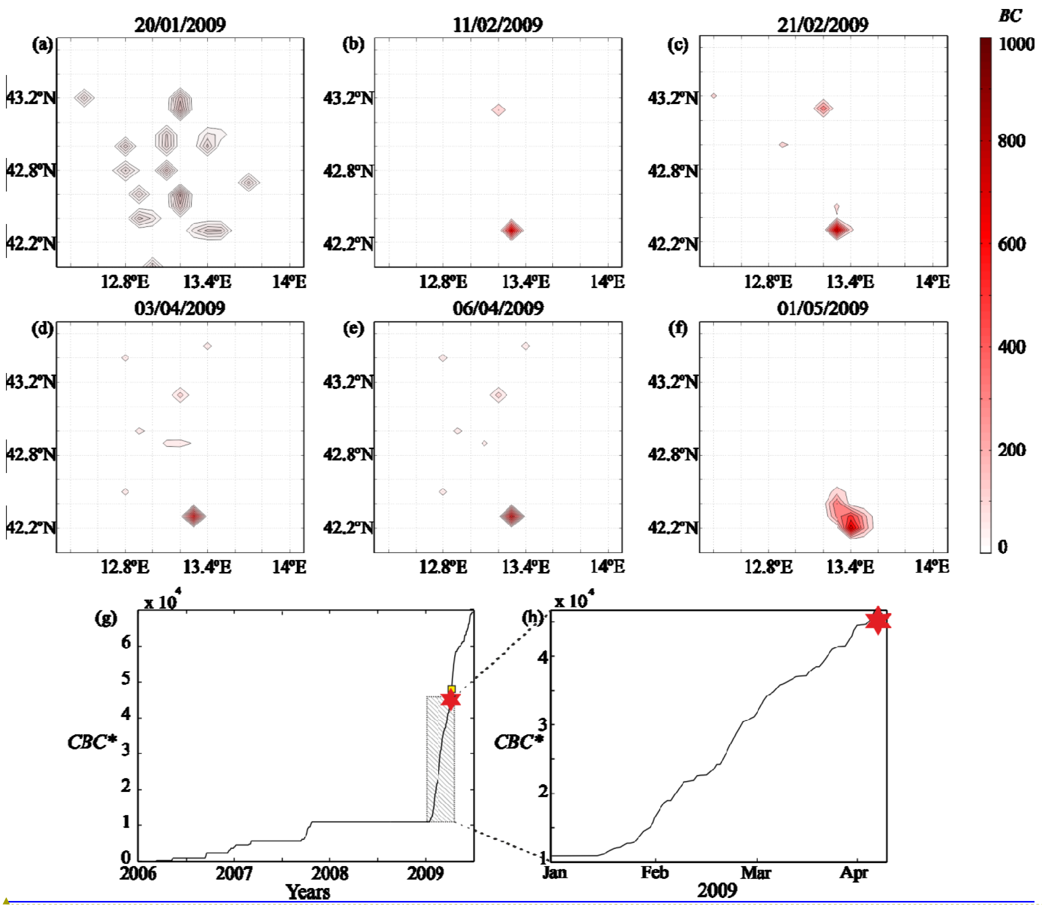

Figure 8. Betweeness cCentrality (BC) computations in the space-window centered at 42.00°N, 13.30°E (off the center of the epicenter) with radius $R_1 = 1^o$. The mainshock occurred on April 6th, 2009 (red star): (a-i) snapshots of the BC maps for each cell from 20.01.2009 to 01.05.2009; (a-e) BC maps before the mainshock. (f) Cumulative BC computed at the mainshock cell (CBC^*) from 01.01.2006 to 30.06.2009 (g), from 01.01.2009 to 06.04.2009 (h).

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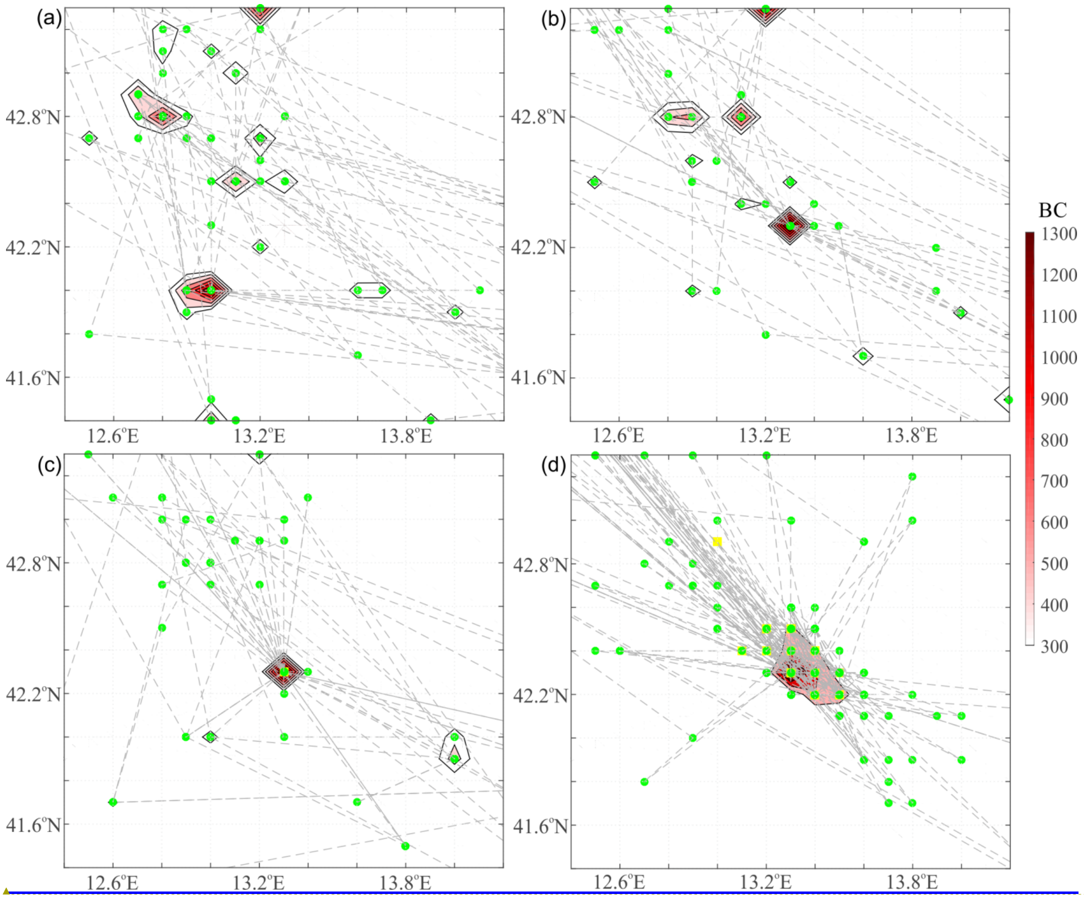

Figure 9. Snapshots of seismic networks overlaid on the ~~projected to the contour plot of~~ ~~b~~Betweeness ~~c~~Centrality (BC) contours for ~~with radius~~ $R_1 = 3^o$ around the epicenter;~~,~~ green squares corresponds to events of $M \leq 3.0$ while yellowsquares corresponds to events of $3.1 \leq M \leq 5$. Dash lines are the edges of the network that connect successive seismic events. The time window for each network is 15 days. (a) From 26 September until 10 October 2008, (b) From 14 to 27 January 2009, (c) From 20 March to 4 April 2009 and (d) From 1 to 16 April 2009.

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