Long-term changes of the glacial seismicity: case study from Spitsbergen

Institute of Geophysics
Polish Academy of Sciences

Wojciech Gajek(1), Jacek Trojanowski (1), Michał Malinowski (1)
(1) Institute of Geophysics, Polish Academy of Sciences

Abstract

Changes in the global temperature balance have proved to have a major impact on the cryosphere and therefore retreating glaciers are the symbol of the warming climate.

Here we explore the possibility of using data recorded by permanent seismological stations to monitor glacial seismic activity. Our study focuses on detecting and recognizing glacier-generated seismic signals and monitoring interannual changes in seismicity of the Hansbreen glacier (Hornsund, southern Spitsbergen) and the Kronebreen glacier (Kongsfjorden. western Spitsbergen) between 2008 and 2014.

To distinguish between glacier- and non-glacier-origin signals with the data from only one seismic station in the area, we developed a new fuzzy logic algorithm based on the seismic signal frequency and the energy flow analysis.

Our automatic event detection and recognition procedure can be used to monitor glaciers' seismic activity. What's more, it has revealed that the number of detected glacier-origin events over the last years has significantly increased. We also observed that the annual events distribution correlates well with the meteorological data.

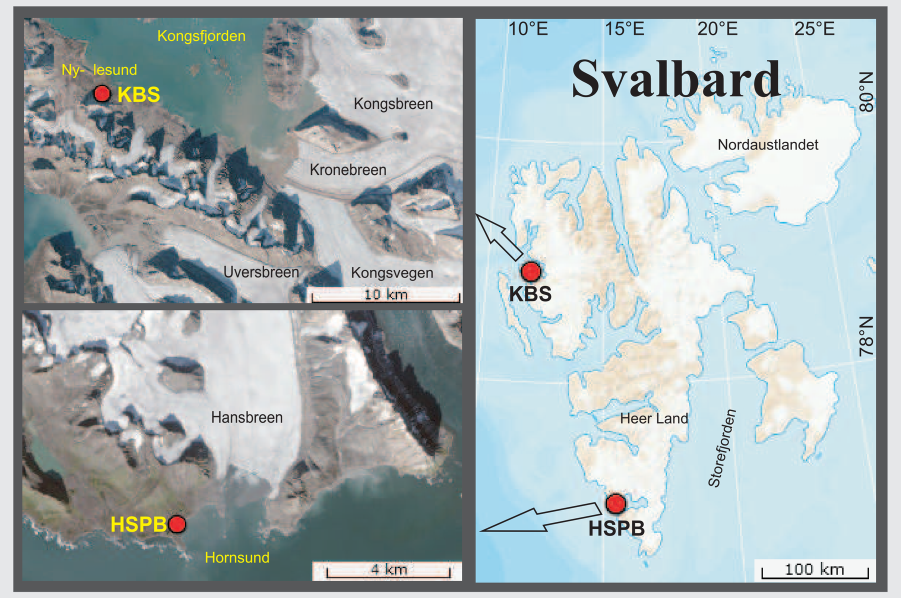


Fig. 1. The study area:
Right hand side – general map of Svalbard with seismological stations KBS and HSPB marked with red dots.
Top left hand side – Enlarged KBS station area. Bottom left hand side – enlarged HSPB station area. Modified from online Map of Svalbard: http://toposvalbard.npolar.no/.

1. Data overview

In this study we use few-years-long seismic records from permanent seismological station located in Spitsbergen, Svalbard.

Seismic events of various origin are expected to occur in the analysed dataset. First of all, signals of glacial origin, which we focus on in this study. Another group consists of signals of earthquakes of local and global origin. Other expected records are of anthropogenic origin, as well as caused by natural phenomena like storms, hails, wind blows, ocean waves or animals. The character of the signal of each kind differ in some parameters like duration or frequency content. In this study we focus on discrimination between glacier-generated and other signals.

Our seismological data treatment scheme is aimed at automation of processing of large continuous data volumes in the context of detecting and classifying glacier-induced seismic events.

The sequence of processing procedures and its parameters were adjusted to produce an autonomous processing sequence, easy to implement for any dataset. Each dataset was processed with strictly the same procedures and parameters in order to provide results which would not be biased by data processing. A general scheme consisted of two steps: I - basic event detection, and II - fuzzy logic event classification.

2. Basic event detection workflow

At this stage five processing steps were conducted:

1. Bandpass filtering between 1 and 15 Hz;
2. Detection based on the ratio of short-term average to long-term average (STA/LTA) of the signal;
3. Multiple detection removal;
4. Elimination of the weakest events with small energy relative to the noise energy;
5. Estimation of the duration times of detected events and elimination of events with duration times larger than 25 s.

Such procedure resulted in the total amount of 8876 detections between 2008 and 2014 for HSPB station (Fig. 2) and 17711 detections for KBS dataset between 2010 and 2014.

2.1 The duration time estimation

To estimate the duration time for each detected event we decided to use modified formula for a Normalized Energy Density (NED) function (Sarma, 1971). Contrary to the original formula our mNED uses a sum of absolute values instead of squares of amplitudes and subtracts a noise function (NF).The mNED function is calculated for each time sample *t* in the extracted 50-second-long record using the equation:

$$mNED(t) = \sum_{n=0}^{t} \left(|x(n)| \right) - NF(t)$$

where *n* is a time sample index. The noise function (NF) is given by:

$$NF(t) = a \cdot t$$

where *a* constant value a is calculated for each day separately. For practical reasons we assumed constant daily noise level, approximated by a linear NF. The effect of NF subtraction is well visible in Fig. 2, where mNED function without FN subtraction rises significantly even in the pre-event time interval (i.e. up to 17 s).

We defined that the time needed for mNED to rise from value of 0.15 to 0.85 is a duration time of an event.

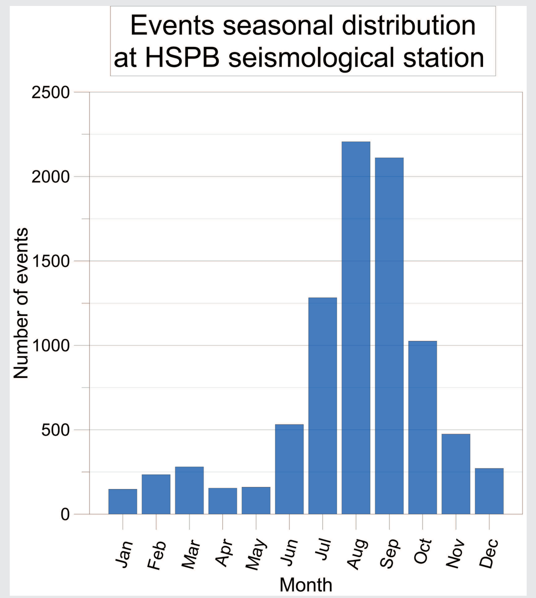


Fig. 2. The seasonal distribution of all detections from the HSPB station in years 2008-2014.

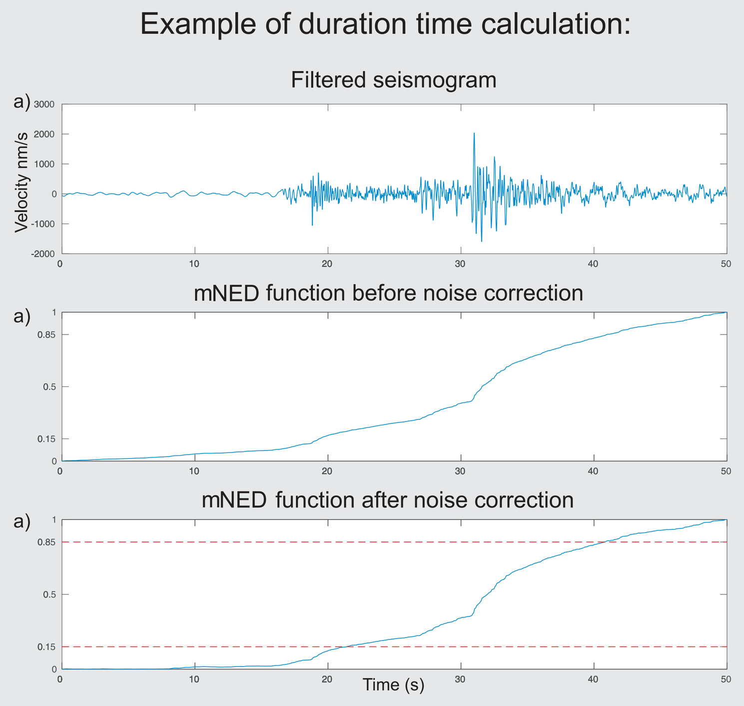


Fig. 3. a) An example of filtered seismogram of an earthquake signal, b) mNED function before NF subtraction for the above seismogram, c) mNED function after noise correction – blue solid line. The mNED limits 0.15 and 0.85 used for duration time estimation - orange dashed line.

3.Fuzzy logic event clasification

The essence of fuzzy logic is to use ranged logical variables instead of standard Boolean (two-valued) algebra. Hence, the fuzzy approach determines to what degree conditions are fulfilled, instead of returning yes-or-no answers. As a result one gets membership functions which say to what degree each object, characterised by chosen variables, belongs to each of the user defined groups with unsharp boundaries (Zadeh, 1965).

We created parameters, which were used to classify all detections into four groups. Classification criteria were adjusted to remove false detections and maximize a match for earthquakes and ice-vibration groups. Events which were not recognized as earthquakes, ice-vibrations or noise were collectively marked as "not identified".

The fuzzy logic algorithm starts with the evaluation how input parameters, individually for each of the events, satisfy the criteria of event classes. Then it chooses the event class which is suited best by those parameters.

3.1 Event classes definition

We defined the following event classes with their respective characteristics:

1. Tectonic earthquake – strong and steady energy flow, which, after exceeding mean value once, remains above it for at least 15 seconds.
2. False detection – strong and short energy bursts exceeding mean value more than at least 7 times in a 50-second-long record.
3. Ice-vibration – signals with dominant frequency band 1 – 5 Hz, lasting from a few to over a dozen of seconds.
4. Not identified – signals not matching any of the characteristics described above.

Output signals characterisitc for each class can be seen it Fig. 4.

3.2 Input parameters

The algorithm was based on four input parameters calculated for each registered event:

1. $p_1 = \frac{P^{f1}_{max} - P^{f1}_{mean}}{P^{f2}_{max} - P^{f2}_{mean}}$
2. $p_2 = \frac{P^{f1}_{max} - P^{f1}_{mean}}{P^{f3}_{max} - P^{f3}_{mean}}$
3. p_3 - a number of time intervals at which $P_{max} > P_{mean}$
4. p_4 - a total length of time intervals longer than 5 s for which $P_{max} > P_{mean}$

where *P* is smoothed power of signal over time and *f1, f2, f3* are frequency bands: 1-5 Hz, 6-10 Hz and 11-15 Hz, respectively. Hence, by e.g. P^{f2}_{mean} mean value of power of the signal in frequency band 6-10 Hz is meant. All used P values were smoothed by running an averaging function over them to get more stable values while calculating *p*. parameters.

3.3 The fuzzy logic classification algorithm output

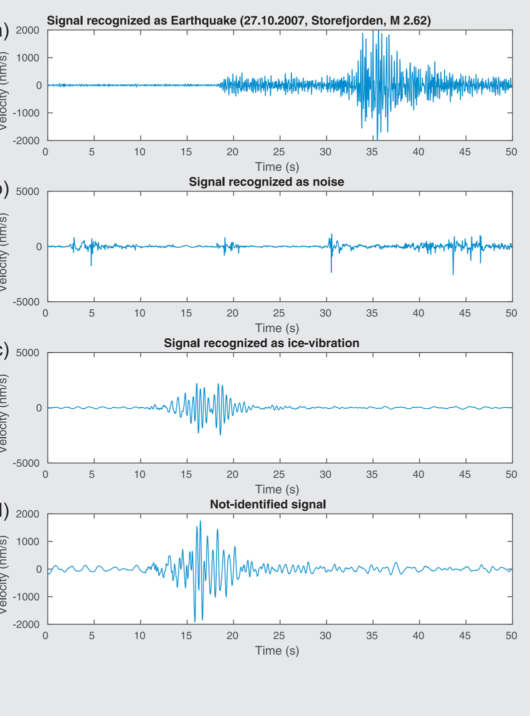


Fig. 4. Seismograms representing each event class: a) a confirmed earthquake signal having epicentre in Storefjorden, b) Noisy detection of unknown origin c) Signal recognized as ice-vibration, d) Not-identified signal

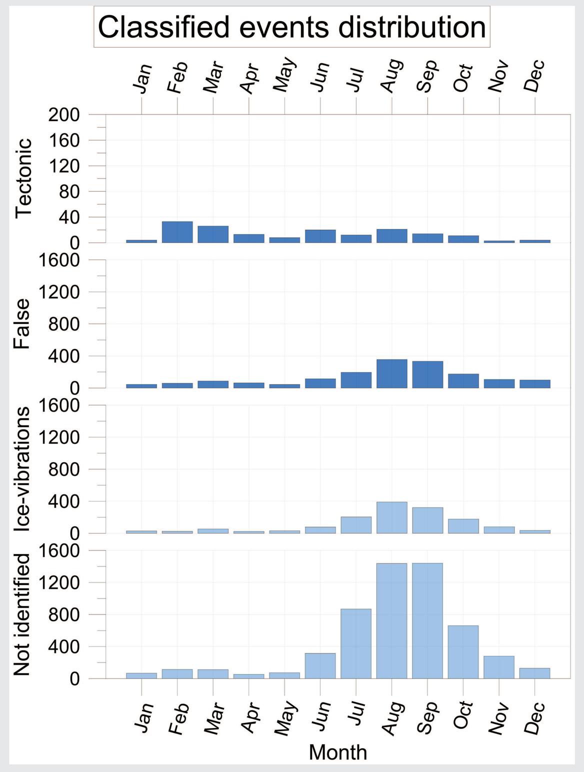


Fig. 5. Seasonal distribution of events in each group from the HSPB station. Light blue coloured groups are affiliated with the glacier-origin events.

4. Results and discussion

We detected and classified over seven thousand events throughout a 7-year-long time span (2008-2014) in the Hornsund region (Fig. 6). From 8876 detections 7020 was identified as glacier-generated.

For Kongsfjorden area 17711 detections throughout 5-year-long time span (2010-2014) was detected and 14913 of them was recognized as glacier related events (Fig. 7).

For both datasets seasonal event distributions follow the same pattern each year. During winter and spring they stay at base-level activity, then intensify from June to November, having its peak in August and September.

-The highest correlation coefficient was found between the seasonal glacier activity and temperature data with one month delay. It reached 0.95 for HSPB and 0.96 for KBS station. That follows theory of key role of the sea temperature in calving processes (Luckan et al. 2015).

-Similar long-term seismic activities for both datasets were obtained independently using KBS and HSPB datesets by Kohler et. (2015), what validates used algorithm.

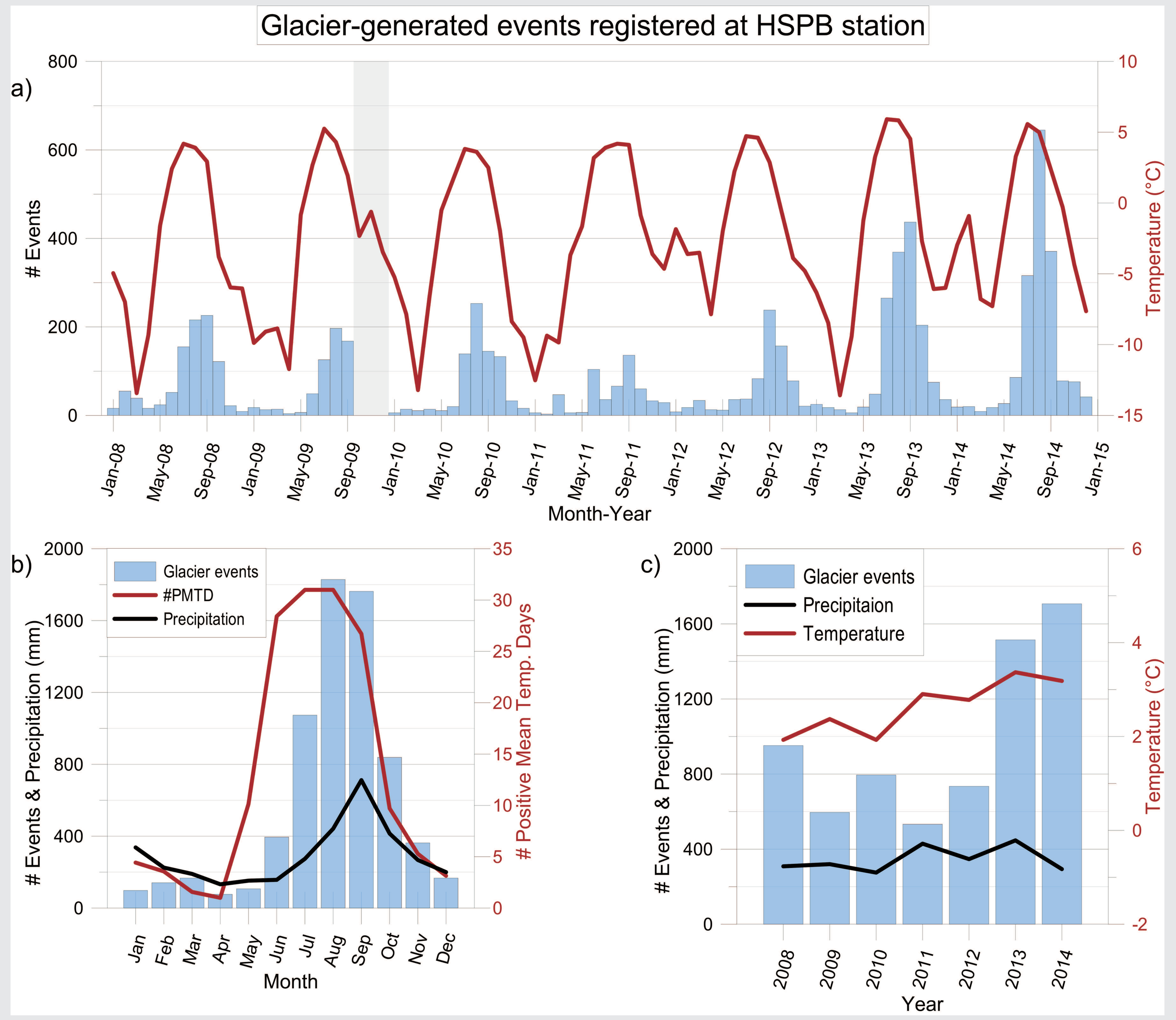
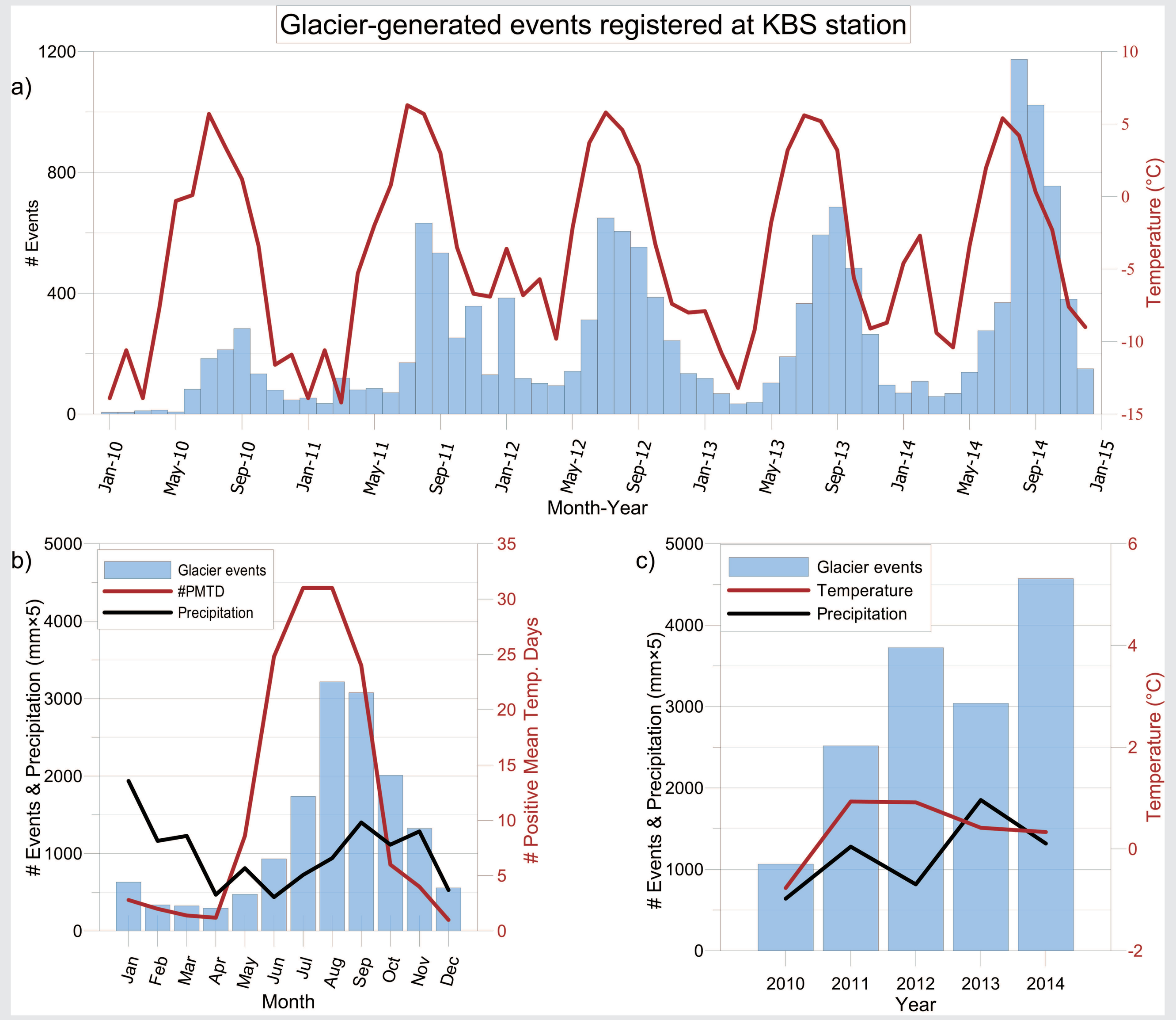


Fig. 6. (the left hand side)
Temporal distribution of glacier-induced events from the HSPB station. a) one-month step distribution; b) monthly distribution of all events summed over 2008-2014, summed precipitation – black solid line, the mean number of days in each month over 2008-2014 with positive mean temperature – red solid line; c) distribution of all events between 2008-2014, summed precipitation in warm months (VI-XI) – black solid line, mean temperature in warm months(VI-XI) – red solid line.

Fig. 7.(the right hand side)
Temporal distributions of the glacier-induced events from the KBS station. a) one-month step distribution b) monthly distribution of all events summed over 2010-2014, summed precipitation – black solid line, the mean number of days in each month over 2010-2014 with positive mean temperature – red solid line; c) distribution of all events between 2010-2014 summed precipitation in warm months (VI-XI) – black solid line, mean temperature in warm months(VI-XI) – red solid line.



5. Conclusions

Glacier related seismic events are recorded by regional seismic stations.

Our automatic event detection and classification algorithm based on fuzzy logic can be used to discriminate between non-glacier and glacier-generated events.

Over recent years the glacier-related seismicity in the analysed regions of Spitsbergen have increased significantly.

The seasonal events distribution correlates best with the seasonal temperature variations lagged by one month.

Our procedure can be apllied for an automatic real time monitoring of glaciers' seismic activity.

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The KBS seismological station belongs to the Norwegian Seismological Network and is maintained by the University of Bergen.

The meteorological datasets come from GLACIO-TOPOCLIM database and eKlima service.

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