Identification of Non-Stationary Turbulent Events for Different Regimes of Stable Boundary Layer Turbulence

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Introduction

Usual approaches which aim to recognize events in the stably stratified atmospheric boundary layer (ABL) assume certain physical processes and then search for a trace of these in atmospheric time series. However, many events in atmospheric time series result from yet unidentified physical processes. A statistical method was recently developed by Kang et al.[3] to detect events in noisy time series without assuming any underlying physical processes. We analyzed this method and applyed it to the SNOHATS dataset which includes long term measurements of turbulent quantities collected in the stable boundary layer.

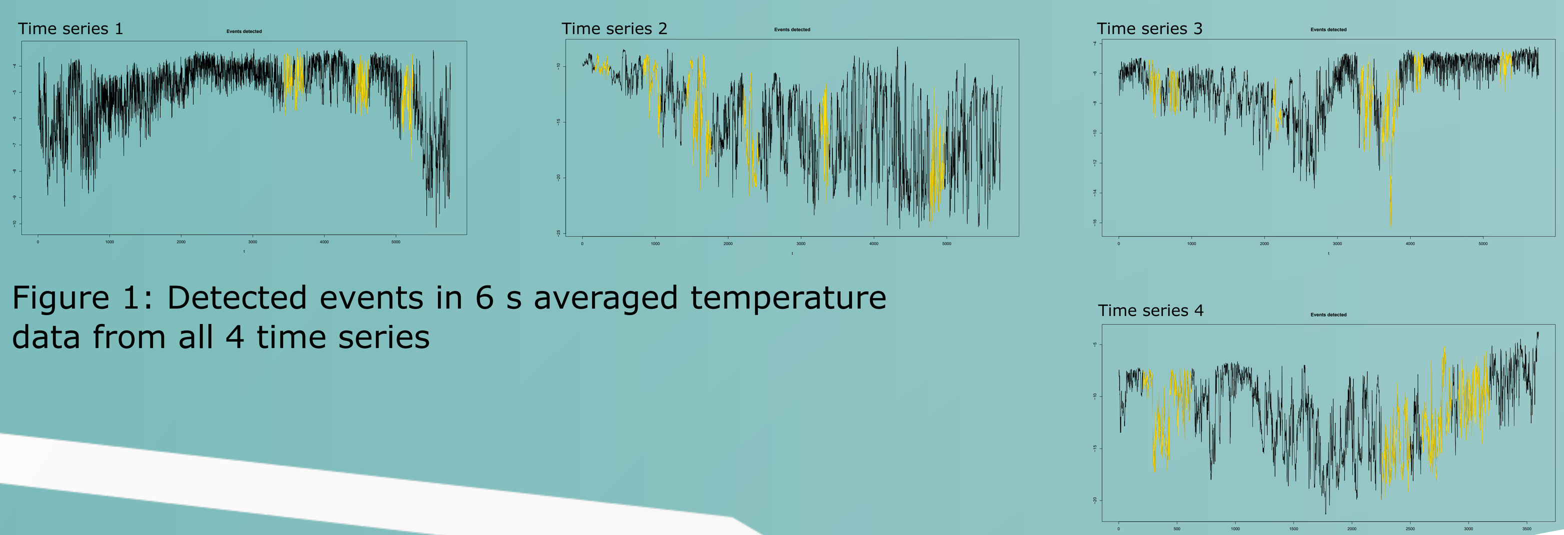


Figure 1: Detected events in 6 s averaged temperature data from all 4 time series

Description of the Data

The SNOHATS data was collected over the Plaine Morte Glacier in the Swiss Alps in 2006 by the EFLUM laboratory at EPFL. This analysis is based on 3D wind velocity component, temperature and humidity measurements of 4 sonic anemometers (5,6,7 and 8) out of 12. We will focus on the wind velocity and temperature dynamics. Figure 2 shows the set up of the sonics. The analysis was based on four timeseries of 8 hour length that were isolated in a study by Vercauteren and Klein
4. Time series 2 and
4 are characterized by being very stable while time series 1 and 3 are weakly stable.

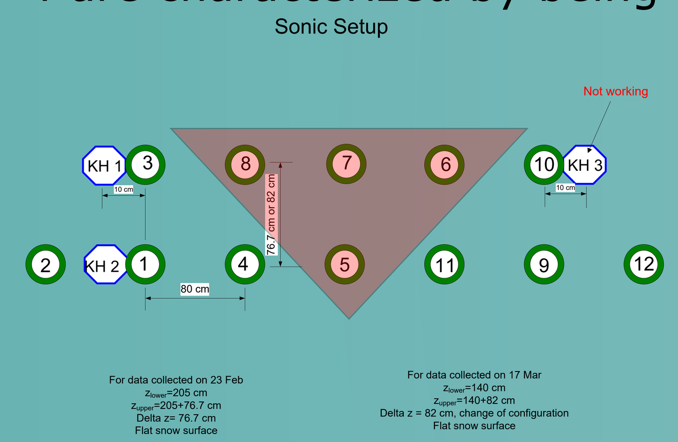


Figure 2: Sonic Set Up
Figure 3: SNOHATS dataset side view of the 12 sonics array

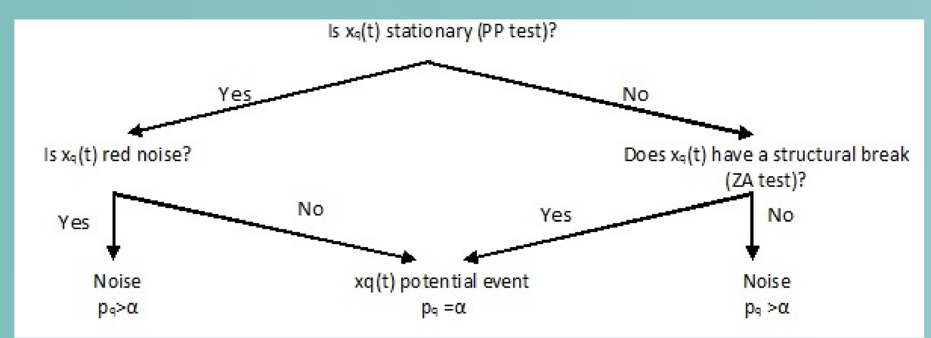
Description of the Method

Goal: To separate nonstationary turbulence events from noise in a time series

Main assumption: Background noise is always present in the time series and events are seperated by noise.

Details: By using a sliding window with predefined length, subsequences are obtained. The event detection method is applied to each subsequence. The event detection is performed on overlapping sequences rather than on seperated blocks.To seperate events from noise, three steps are performed on these subsequences. Figure 4 shows the order in which the tests are applied to each subsequence. First the Philip Perron (PP) test is applied to the subsequence and it checks if the subsequence is stationary. If it is stationary, according to the Philip Perron test, the Zivot and Andrews (ZA) test is performed. Otherwise the noise test is performed after the Philip Perron test. Events are defined as those subsequences which are significantly different from pure noise. Before starting the noise test, the type of noise has to be chosen. Stationary turbulence and red noise can be well represented by an AR(1) process. Hence, we used red noise.

Figure 4: Flowchart of the event detection procedure for a subsequence of a time series of turbulence data



Results

The choice of the time window length, which is directly linked to the length of the posible events, is so far made subjectively and is based on experience and context. This could be solved by using a different method which determines the relevant time scales, before applying the event detection procedure. Another option which was used is a multiscale approach. A multiscale analysis allows a verifiable choice of the scale, if it cannot be determined in a different way. We analyzed submesomotions which we definded as motions from 1 to 30 minutes. Figure 5 shows the results of the multiscale approach.

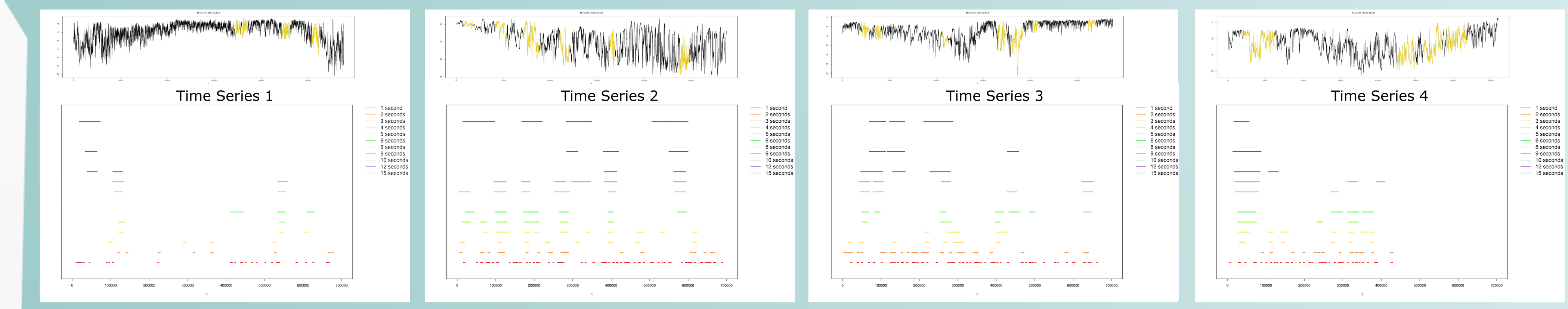
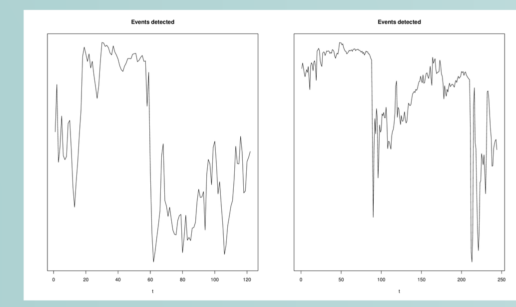
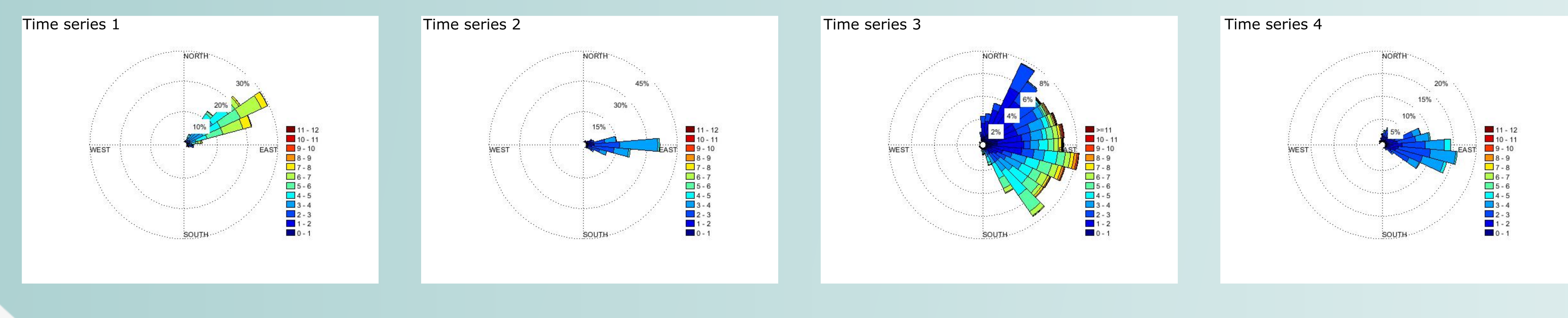


Figure 5: Multiscale approach: The lines show the time periods recognised as events for different averaging times ranging from 1 second to 15 seconds.

The results point to a large sensitivity of the method to the scale at which it is applied. In time series 4 the detected events in the higher averaged data tend to be more to the beginning of the time series. Contrary, in time series 2 they are more evenly distributed over the whole time period. It is noticable that the weakly stable time series 1 and 3 have shorter and less events than the very stable time series 2 and 4. In general, the 6 s averaged data is a sensible choice because the detected events from the 6 s averaged data overlap the most with events from lower and higher averages. The following figure gives examples of possible events.



To check if there is a relation between mean wind speed and wind direction we look at the wind roses for all time series (Figure 6).



The colour shows the wind speed and the length shows the frequency of a wind direction. Based on the wind rose plots we can conclude that in time series 2 and 4 the mean wind is slow while in time series it is faster. The wind direction is more stable in time series 2, and variable in cluster 4 mainly for slow wind events.

Conclusions

▪In the two very stable time series there was a higher number of nonstationary events detected which were also longer and the mean wind was slower. Contrary in the weakly stable time series there was a lower number of detected nonstationary events and they were shorter. The mean wind for these time series was higher.

▪The method was determined to give reliable results because we were able to compare the results from the measurements of one sonic with the results from three neighbour sonics. Most events were detected in all four measurements.

▪**Limitations:** The results from the event detection method by Kang et al.[3] is sensitive to the scale at which it is applied.

▪**Solution:** A multiscale approach is an option to work around this scale dependency. In general, the multiscale approach is a good way to identify which average and time window gives the most reasonable output.

[3] Kang, Y., D. Belusic, and K. Smith-Miles, Classes of structures in the stable atmospheric boundary layer, Q.J.R. Meteorol. Soc., doi: 10.1002/qj.2501
[4] Vercauteren, N., and R. Klein, A Clustering Method to Characterize Intermittent Bursts of Turbulence and Interaction with Submesomotions in the Stable Boundary Layer, Journal of the atmospheric sciences 72(4): 1504–1517, doi: 10.1175/JAS-D-14-0115.1

Scaling Cascades in Complex Systems

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