Connecting a large database of debris flow events in Austria with daily precipitation data

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1 Introduction

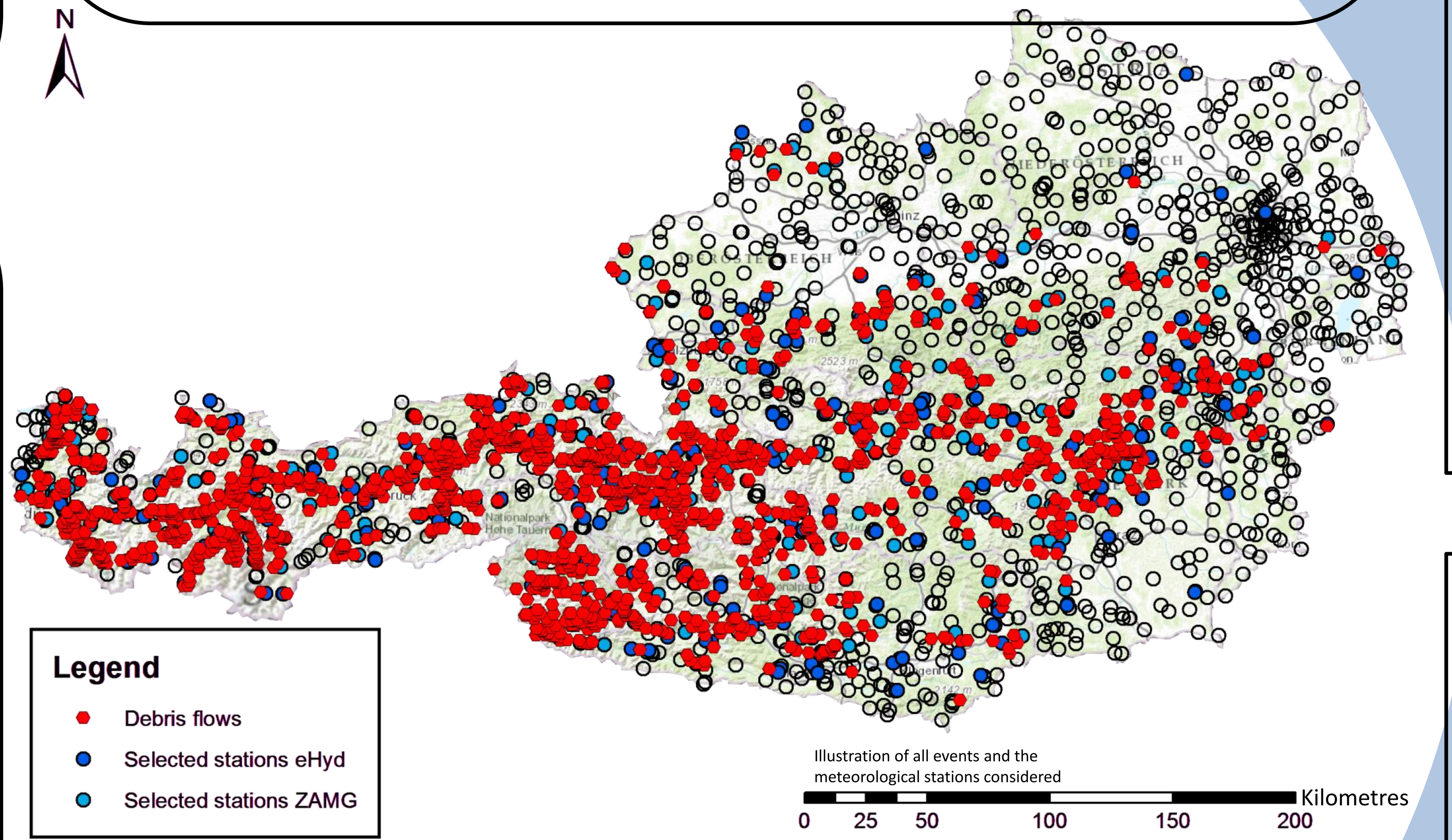
Debris flows represent a severe hazard in Alpine countries and can pose a threat to lives and values at risk. Previous studies have shown that debris flows are mainly controlled by climatic factors (e.g. Stoffel et al. 2013).
In Austria debris flows are mostly initiated by either intensive, localized thunderstorm events or long lasting low-pressure systems (advective precipitation). This leads to the need for a better understanding of the causal relationships of parameters connected to precipitation. Furthermore, the identification of such meteorological trigger conditions is of high interest (Gobiet et al., 2013) for improved forecasting of debris flow hazards and estimation of potential impacts due to climate change. In this study we connect a large data base of past debris flow events with daily rainfall and temperature data to investigate trigger conditions and assess possible temporal variations in the frequency of occurrence.
For each event we investigate daily rainfall data of all meteorological stations and choose that nearest station which recorded reliable data before and during the day of debris-flow occurrence.

Is it possible to find patterns in meteorological data to get a rough idea about effects on debris flow initiation?

2. Study area and data

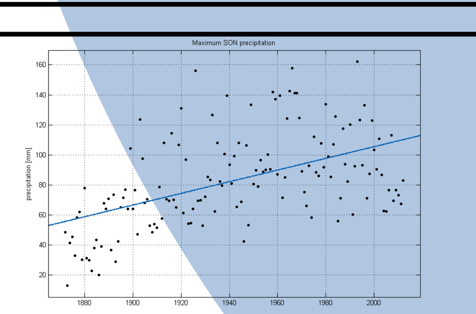
- The study area consisted of all debris flows occurring in the republic of Austria from 1900 until 2008, which are indicated by the red hexagons in the map on the right.
- In total, 2412 documented debris flow events and data distributed over a region of approximately 80,000 km² were available for investigation.
- A worldwide unique hazard-database (IAN) was merged together with two datasets with daily precipitation data. The provided datasets consisted of 2412 debris flows and a total of 1649 meteorological stations.
- 220 ZAMG and 233 eHYD Stations could be selected for the analysis of 2335 of the 2412 debris flow events.

553 meteorological stations were used for investigating 2335 debris flow events occurring from 1900-2008.

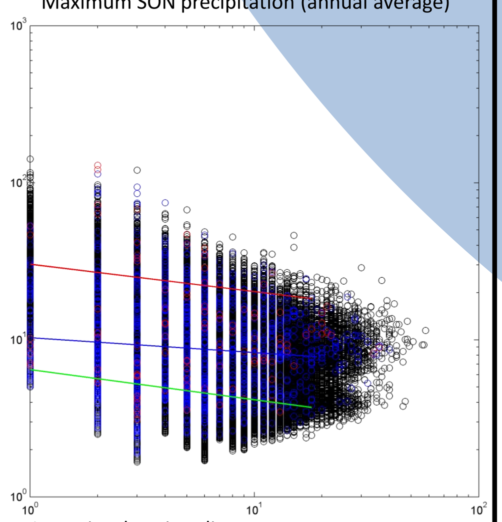


3. Analysis of precipitation

- Precipitation data was first analysed to prepare the dataset for investigation of potential climatic shifts in the occurrence of debris flows (Stoffel et al., 2011).
- The data was homogenised, seasonal maxima, and minima computed to detect overall trends.
- Statistical measures of tendency were used to investigate 30-year shifts in precipitation and debris flow data (3 x 30yr windows).
- For investigation of precipitation thresholds an algorithm provided by M. Berti (Berti et al. 2012) was provided and adapted to the MatLab routines used in this project
- Antecedent precipitation was computed for two ranges (15 and 30 days).



Maximum SON precipitation (annual average)

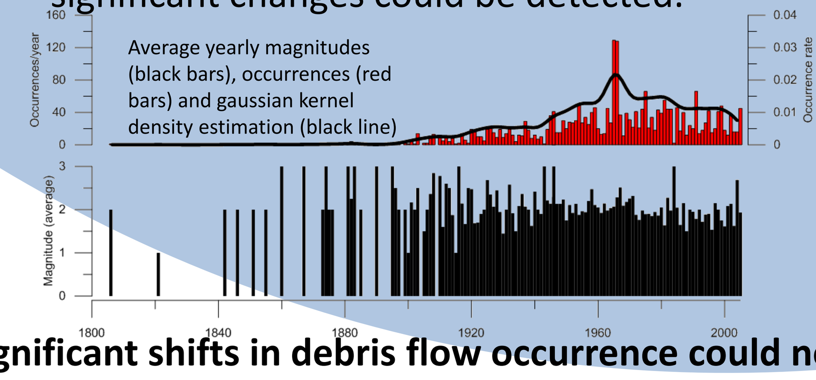


Intensity-duration diagram
(circles: black= total rain, blue = event rain, red = very large debris flows;
lines: green 10%, blue= running mean of 45 and 55 precentile, red = 90%)

There is a clear trend for some, but not for all precipitation signals. Precipitation is difficult.

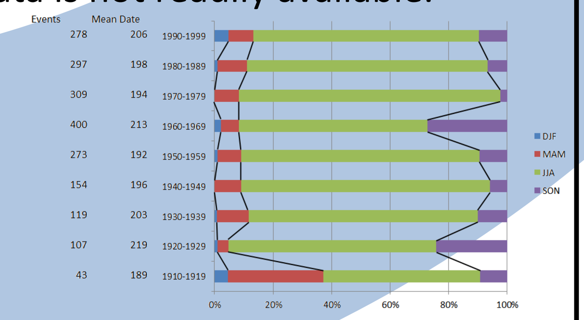
4a. Potential shifts

- General potential shifts in debris flow ocurrence were analysed through kernel density estimation (KDE).
- There is a problem with data thinning when looking at long-term hazard inventories (Mudelsee et al., 2003).
- Shifts in the seasonal occurrence (mean Julian day) were analysed but no significant changes could be detected.



4b. Potential climatic shifts

- Large scale debris flows are more likely to be triggered by long-term advective rainfall.
- It is difficult to provide a general statement for the whole area. Variability is high and time series as well as debris flow data is not readily available.



Analysis of seasonal shifts

Significant shifts in debris flow occurrence could not be detected. This is probably due to the high variability of the characteristics of precipitation because of scale and orography.

5. 1-D Bayesian analysis

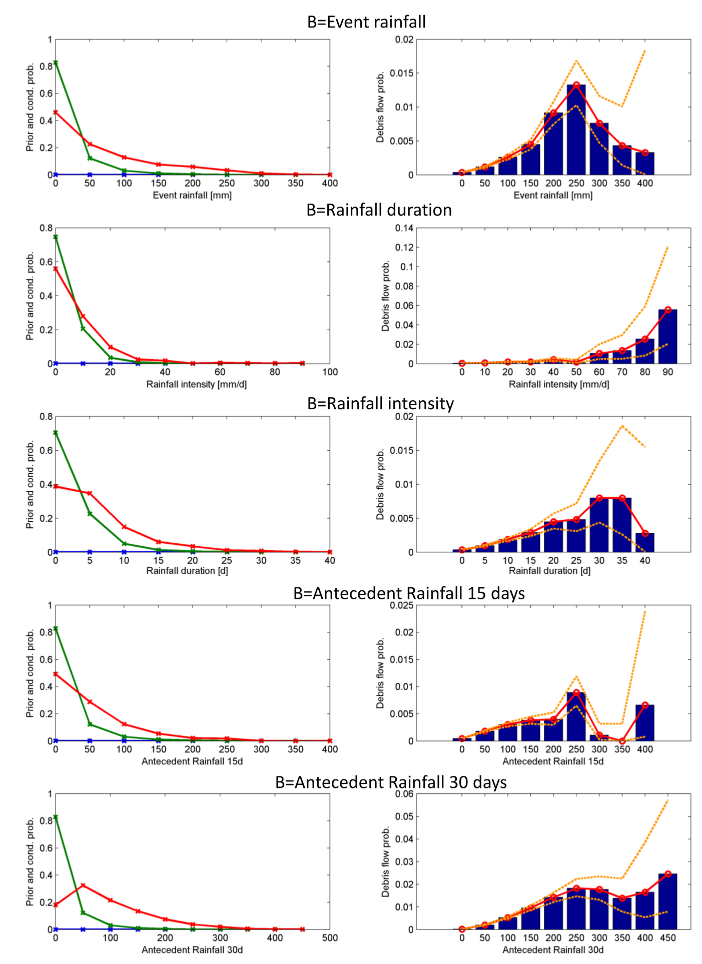
Because no significant shifts could be detected, the whole dataset was analysed to detect the significant parameters with regard to precipitation and debris flows.

For all 2412 events the cumulative precipitation was plotted and the start and end of the rainfall was defined. With this data, the rainfall detection algorithm (Berti et al 2012) could be trained to find typical triggering event rainfalls (TER) in the whole precipitation dataset.

This helped to aqcuire substantiated values for the total amount of TER-events within the considered time frame.

By classification of potential TER, actual TER and threshold classes, Bayes' theorem could be applied:

$$P(A_j|B) = \frac{P(B|A_j)P(A_j)}{P(B)}$$



One dimensional Bayesian analysis considering event rainfall (cumulated rainfall over a defined precipitation event), duration, intensity and two lengths of antecedent rainfall
The figures on the left show prior probability P(A) (blue), marginal probability P(B) (green), and conditional probability P(B|A) of observing rainfall of magnitude B when a debris flow occurs (red). The figures on the right show conditional landslide probability. Uncertainties are calculated from the 95% confidence intervals from Poisson counting errors (Number of debris flows).

Long-term antecedent rainfall has the highest influence on debris flow initiation, rainfall duration and intensities are key factors.

6. 2-D Bayesian analysis

Instead of interpreting singular propositions for A with respect to evidence B it is advisable to use the information gained from computing posterior probabilities to combine parameters of interest for different characteristics.

By doing so it is possible to obtain the conditional probabilities for a space defined by two criteria.

In our case this is the conditional probability of a debris flow occurring when rainfall intensity $i = \log_{10} I$ [mm]

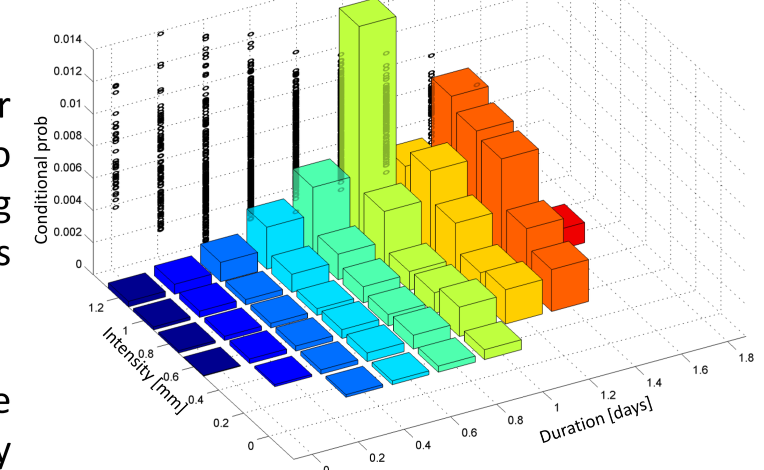
$$i_i \le i < i_{i+1} \text{ with } i_{1:n} = \{0{:}\,0.2{:}\,1.2\}$$

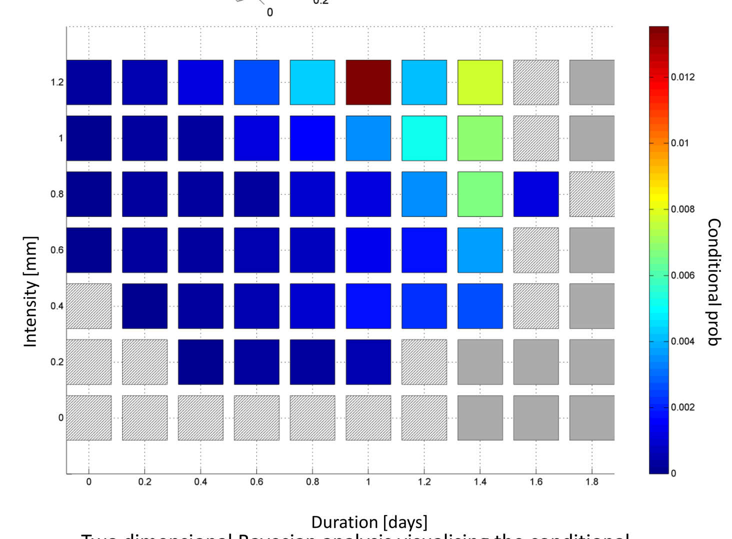
and when duration $d = \log_{10} D$ [days]

$$d_d \le d < d_{d+1} \text{ with } d_{1:n} = \{0{:}\,,0.2{:}\,1.8\}$$

with $i, d \in A$.

If different debris-flow magnitudes are computed separately, the results on the right are even more pronounced.





Two dimensional Bayesian analysis visualising the conditional probability of an event occurring when being in a specific intensity – duration class. E.g. The red square shows, that for 1≤duration<1.2 and 1.2≤1.4 intensity (both logarithmic) the conditional probability is about 0.0012.

In combination with rainfall intensities, there is a clear pattern in favour of advective rainfall as the main factor for debris flows in Austria.

7. Conclusions and outlook

- The current dataset has to be extended into a representative and non-biased data base to better examine possible seasonal shifts and the influence of precipitation on debris flow magnitude
- The one-dimensional Bayesian analysis showed high impacts of event rainfall, the relationship is especially true for large debris flows.
- Due to the very heterogeneous topographic conditions in Austria and thus the high variability of precipitation, the main signals are hard to categorise.
- Two-dimensional Bayesian analysis helped to give a first estimation of the dimensions as well as the categories which are the main factors in debris flow initiation

Next step: Analysis of clustered regions of homogenous precipitation and identification of individual regional thresholds.

Literature
Berti et al., 2012, *J Geophys Res* 117 F04006, p.1-20.
Gobiet et al, 2013, *Sci Total Environ*, *in press.*, p.1-14.
Muddelsee et al., 2003, *Nature* 452, p.166-169.
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