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Climate-Related Analyses along the Austrian Railway Network, Part II: Climate Indices based on Recorded Damage Events

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Abstract

The geo-coded hazardous event data base, whose establishment is lined out in part I of this three-paper-series – whereby we have focussed in the project 'clim_ect' on the following hazard categories: (i) flooding, (ii) mudslide, (iii), wind-storm, (iv) falling rock, (v) snow – has been blended with meteorological data (used as predictors in the modelling of hazard occurrences). This has allowed to calibrate and validate a model based on empirical orthogonal functions (EOFs) in T-mode to derive pertaining hazard trigger patterns (HTPs).

A specifically designed validation procedure that is being based on a substantial amount of bootstrapped train/test subsets allowed the identification of optimal hazard-category-sensitive-parameter-settings most suitable for subsequent calculations of hazard-specific HTPs. This procedure has lead to the following model parameters: 3 EOF patterns, a temporal window of 7 days, and category-dependant predictors out of daily precipitation totals (RR), minimum daily temperature (Tn), and daily average air pressure (P) as follows (enumeration corresponds to the hazard categories from above): (i) RR, (ii) RR, (iii) P, (iv) Tn, RR, (v) Tn, RR. Derived parameter values turn out to be consistent with expert knowledge.

Due to the limited scope of this short paper, two hazard categories are outlined in detail: mudslide and flooding. In case of mudslide, comparably high precipitation totals the day prior an event seem to carry decisive importance (first EOF). Target-day (the day on which a hazard event occurred) precipitation sums (second EOF) and the amount of soil-prehumidification during the week before events (third EOF) carry some significance too. In the case of flooding, the first EOF highlights the importance of continuous daily precipitation events during the week preceding events, without putting much weight on the temporal order of daily totals. The second EOF indicates the importance of pre-moistening effects. The third EOF points toward the relevance of precipitation on the day before the events emergence.

Detected HTPs can be used in order to identify similar sequences in ensembles of future downscaled climate change projections, which is an extension of the described work in this paper towards an assessment of future changes in risk landscapes. Such approaches permit for quantitative assessments of developments concerning weather-driven damages that, in turn, may serve as objective foundations for setting up suitable adaption programs and protection measures.

Keywords: climate analysis, climate impact, climate adaptation, hazard trigger patterns, railway network, hazard events.

1 Introduction

The perception and awareness of stakeholders regarding the impact of transport on climate through greenhouse gas emissions as well as transport's vulnerability against climate change induced hazards has increased significantly in recent years. Due to this dual role, mitigation measures (focusing on the elimination of greenhouse gas emissions) need to be complemented by adaptation efforts (reducing the vulnerability of the transport sector by increasing its resilience to climate change related damage events).

Weather triggered damage processes (e.g. falling rocks or floodings) causing down-times and closures of railway networks for repair works as well as disturbances and delays are expected to alter in frequency and magnitude along with climate change.

The identification of such weather sequences and the derivation of their future alterations state an essential basis for designing appropriate adaption programs. The research project 'clim_ect' aims at setting up an end-to-end pipeline from consistently compiling hazard data to the generation of adaptation management plans based on ensembles of climate change projections. This endeavour is presented through three short papers, which cover:

1. the generation of a standardized hazardous event data base along the Austrian Railway Network;
2. the derivation of hazard trigger patterns (HTPs) describing weather sequences that trigger hazard events;
3. the development of future hazard management plans and mitigation measures.

In this paper, the second part is addressed.

A key step in establishing future hazard development corridors (HDCs) is the derivation of hazard trigger patterns (HTPs) associated with them. This may be done subjectively based on expert knowledge through the definition of certain thresholds (e.g. precipitation thresholds for a number of days until considered hazard events take place, see [1]), or objectively by applying multivariate statistical techniques linking observed weather developments to these hazard occurrences.

Within 'clim_ect' the latter approach is pursued (see [2] for a detailed description of the derivation of HTPs). The compiled dataset (see part I of the three short papers mentioned above) allows for the statistically robust calculation of HTPs referring to the following hazard categories: (i) flooding, (ii) mudslide, (iii), wind-storm, (iv) falling rock and (v) snow. Further categories (see part I) feature too few observations to warrant statistically sound derivations of associated HTPs. In the extent of this short paper the focus is set on the first two hazard categories: flooding and mudslide.

2 Methods

The process of establishing hazard trigger patterns (HTPs) is two-fold: (1) the conduction of a validation procedure to identify optimal parameter-sets needed in the HTP model per hazard category, and (2) the actual HTPs by applying the validated models.

The objective determination of HTPs can be achieved through Empirical Orthogonal Functions (EOFs, see e.g. [3]) depicting meteorological observations used as predictors (e.g. precipitation totals, temperature, pressure). This involves solving eigenvalue problems corresponding to covariance matrices made up by the predictors in consideration. Resulting EOF patterns represent the eigendirections of respective eigenvalue problems. These pattern may extend in temporal or spatial dimensions (EOFs in T-mode or S-mode, respectively). Here T-mode EOFs – resembling the sought HTPs – are considered. The principal components (PCs) associated with the

EOFs represent events that allow – through comparison with actual observations – to validate different hazard modeling approaches.

For the two hazard categories mudslide and flooding, daily, gridded precipitation data (predictor variables) are retrieved from SPARTACUS (see [4,5]). For each recorded hazard event, averages over the closest SPARTACUS grid point and its four nearest neighbours in space are considered on the day the hazard occurred (target-day) and for a number of preceding days, where the latter is one of model parameters to be optimized. These precipitation sequences are combined to form a N by T matrix, where N is the number of hazard event occurrences and T the number of days in consideration per event. A singular-vector-decomposition algorithm is used to derive the corresponding EOFs and PCs, which represent the so-called hazard trigger patterns.

The model validation (1) was achieved by applying a bootstrapping algorithm that permitted to validate the optimal (i) set of predictors, (ii) the number of EOFs taken into account, and (iii) the length of the temporal window preceding hazardous events. A subset of the predictor data intersected with the hazard event data (preprocessed matrices) and a subset of randomly drawn predictor data -- representing the test set -- were each projected onto the EOF patterns, that were derived from a training set beforehand. Thereby, sets of pseudo principal components (PPCs) are generated. Data splits were 80/20, for train/test respectively. Bootstrapping was repeated 1000 times and the root mean square error (RMSE) between the test PPCs and the PCs from the 'true', underyling data served as evaluation metric.

The optimal parameter set (2) deduced in the validation process is then used to calculate HTPs for every category.

3 Results

Resulting model parameters (1) for the calculation of HTPs are shown in Table 1. Optimal temporal window lengths for modelling floodings and mudslides stretch 3, 5, and 7 days. Finally a window extending over 7 days was chosen. This decision was made in order to be in line with [2], which is based on a more comprehensive data set, and because the RMSE values (which are employed in the evaluation metric) associated with these three parameters are almost the same (±0.04 difference on a normalized RMSE). The number of EOFs found to be relevant was consistently equal to 3 for all hazard categories. As for the categories falling rock as well as snow, models incorporating temperature- and precipitation-based predictors yielded best results.

Parameter\Category	Flooding	Mudslide	Wind-Storm	Falling rock	Snow
Temporal window [days]	7	7	7	7	7
Number of EOFs	3	3	3	3	3
Predictors	RR	RR	P	Tn, RR	Tn, RR

Table 1: Optimal model parameters to be used in HTP calculations resulting from validation experiments. RR refers to daily accumulated rain rates, Tn to daily minimum temperature and P to air pressure (interpolated onto the same pressure level for different stations).

Hazard trigger patterns (2) for the categories mudslide and flooding are depicted in Figure 1. In case of mudslide, comparably high precipitation totals the day prior an event seem to carry decisive importance (first EOF). Target-day precipitation sums (second EOF) and the amount of soil-prehumidification during the week before events (third EOF) carry some significance too, whereby the latter lessens with increasing distance back in time. As for floodings, the first EOF highlights the importance of continuous daily precipitation events during the week preceding events, without putting much weight on the temporal order of daily totals. The second EOF indicates (rather comparable to the third EOF in case of mudslides) the importance of pre-moistening effects. The third EOF points toward the relevance of precipitation on the day before the events emergence. The principal components on the right-hand side (b, d) show that there are outlier events with heavily strengthened magnitudes, but the relative importance between the principal components stays the same, therefore solidifying the analyzed trigger patterns.

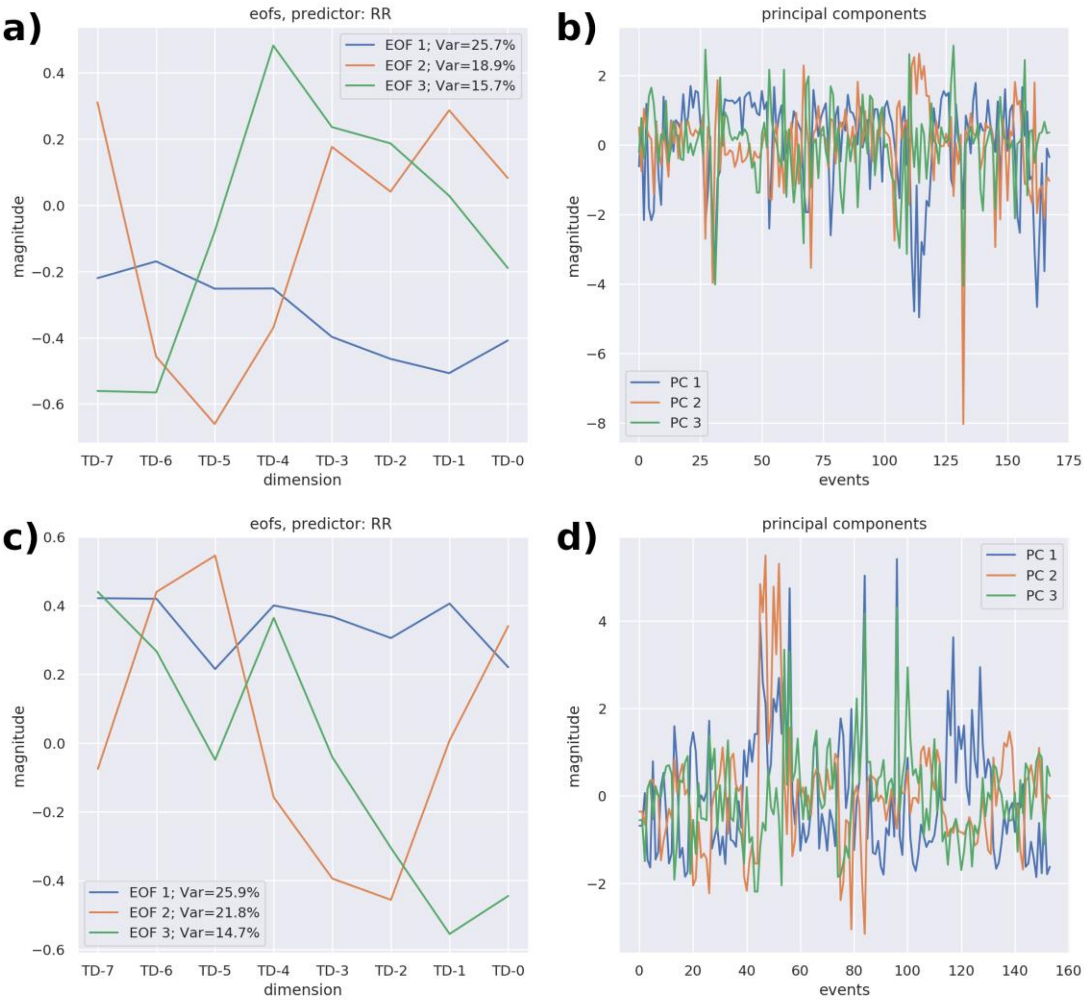

Figure 1: Hazard trigger patterns (a, c) and principal components (b, d) for mudslide (top row) and flooding (bottom row). Explained variances are indicated in the legends. Interpretation can be found in the body text.

4 Conclusions and Contributions

The geo-coded hazardous event data base, whose establishment is lined out in part I of this three-paper-series – whereby we have focussed here on the following hazard categories: (i) flooding and (ii) mudslide – has been blended with meteorological data (used as predictors in the modelling of hazard occurrences). This has allowed for the statistical robust derivation of pertaining hazard trigger patterns (HTPs).

A specifically designed validation procedure that is being based on a substantial amount of bootstrapped train/test subsets allowed the identification of optimal hazard-category-specific model parameters suitable for subsequent calculations of hazard-specific HTPs. Derived parameter values turn out to be consistent with expert knowledge in terms of various weather sequences triggering different hazard events jeopardizing several ecological, social and economic systems. This is in line with previous work ([2]) and supported by the results given by the above described validation procedure.

Detected HTPs can be used in order to identify similar sequences in ensembles of future downscaled climate change projections (see [6]), which is an extension of the described work in this paper towards an assessment of future changes in risk landscapes. Such approaches permit for quantitative assessments of developments concerning weather-driven damages that, in turn, may serve as objective foundations for setting up suitable adaption programs and protection measures.

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