On the nexus between landslide susceptibility and transport infrastructure – agent-based vulnerability assessment of rural road networks in the Eastern European Alps

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Abstract. Road networks are complex interconnected systems. Any sudden disruption can result in debilitating impacts on human life or the economy. Interruptions of the transport flow may lead to potentially severe consequences in terms of both direct and indirect losses. In particular, road systems in mountainous areas do not feature redundant elements at comparable economic efficiency. Therefore, assessment of network vulnerability is of major importance for guaranteeing the smooth functioning of

5 societies, especially in those regions.

Among various menacing hazards, landslides protrude as particularly destructive events jeopardizing the integrity of land transport systems by causing structural damage and network interruptions. The aim of this paper is to present how road infrastructure is vulnerable towards landslides events, with emphasis on the consequences for the affected road users. This is addressed on the Austrian region Vorarlberg, which allows cross-learning and cross-comparison of, for example, rural and

10 urban areas, also at different scales. The focus of this case study is on resilience issues and support for decision making in the context of a large scale sectoral approach.

By taking into account derivates of a high-resolution digital terrain model as well as geological properties, a landslide susceptibility map of the test region is derived by means of the weight of evidence method. This susceptibility map is concatenated with historic data of landslide inventories and a digital road graph in order to identify critical sections of the road network. Sub-

15 sequently, effects of interruptions of the road network at these critical links are analyzed by applying a mesoscopic multi-agent transport simulation model.

Results show the merits of using agent-based traffic modeling for assessing the impacts of road network interruptions on rural communities by providing insight into the characteristics of the population affected, as well as the effects on its daily routine in terms of detour costs.

1 Introduction

Transport networks and its related assets support the delivery of essential services to society (European Commission, 2017; Mejuto, 2017; Gutiérrez and Urbano, 1996). The functionality of socio-economic systems in modern communities heavily depends on the extensive, interconnected networks of critical infrastructures to such an extent that any disruption may cause

5 rippling effects, eventually entailing instability of the whole infrastructure network – both domestically and beyond (Bíl et al., 2015; Jaiswal et al., 2010).

There is a growing amount of studies on roads being impassable and damaged by natural hazards such as flash floods (Pregnolato et al., 2017), landslides (Winter et al., 2016) or fallen trees (Bíl et al., 2017). Simultaneously, media coverage on these incidents increased (e.g. NZZ, 2018; ORF, 2018a, b; Tiroler Tageszeitung, 2018). The impacts caused by such severe

10 weather events and associated hazards underline the importance of climate resilient transportation infrastructure, especially in complex landscapes such as the European Alps. Failure and disruption of infrastructure can affect the whole society and the environment due to cascading effects which result from the dependence of economies, institutions and societies on transport networks (Kellermann et al., 2015; Doll et al., 2014; Keller and Atzl, 2014; Pfurtscheller, 2014; Meyer et al., 2013; Kappes et al., 2012). This is especially true under severe weather conditions, triggering disasters, because reliable networks are crucial

15 for averting further damage, saving lives and mitigating economic losses. Therefore, the overall societal loss introduced by destructive incidents exceeds the mere physical damage to the infrastructure by far. Apart from impairment of roads – which results in maintenance and reconstruction efforts to be carried out by road operators (c.f. Donnini et al., 2017) – secondary aspects of damage to infrastructure networks have to be considered in a broader economic context. Intangible and indirect costs, which are caused by e.g. detours or delays, may even surpass the mere infrastructural damage (Klose et al., 2015; Pfurtscheller

20 and Thieken, 2013; Meyer et al., 2013).

Consequently the assessment of transport network systems has gained relevance in academia as well as the policy agenda of authorities across all scales. Some triggers were the influential terrorist attacks in recent years, maybe starting with the "9/11" incidents in New York in 2001, and manifested later during the 2004 Madrid train bombings or the 2005 London attacks. Moreover, natural hazard events such as hurricanes Katrina or Harvey in the United States, the 2007 UK Summer

25 Floods or the 2013 Danube floods in Central Europe also revealed the susceptibility of transport infrastructure. All these events affected larger areas, considerably disrupting the traffic system (Bíl et al., 2017; Rupi et al., 2015; Jenelius, 2009; Taylor et al., 2006; D'Este and Taylor, 2003; Berdica, 2002). Their impacts created negative socio-economic consequences (high direct and indirect losses) to European societies (Rheinberger et al., 2017; Kellermann et al., 2015; Pachauri and Meyer, 2014; Schweikert et al., 2014; Pfurtscheller, 2014; Meyer et al., 2013; Pfurtscheller and Thieken, 2013; Nemry and Demirel, 2012; Rheinberger,

30 2011; Koetse and Rietveld, 2009).

Major losses were caused by disrupting services, the flow of crucial goods and supply chains (Pfurtscheller and Vetter, 2015; Taylor and Susilawati, 2012; Jenelius, 2009). Since no context-free definition of road network vulnerability exists, respective methodological approaches (even if highly sophisticated) remain fragmentary and repeatedly tailored to individual settings (Bagloee et al., 2017; Eidsvig et al., 2017; Mattsson and Jenelius, 2015; Rupi et al., 2015).

Berdica (2002, p.119), for example, suggests that network vulnerability should be understood as 'susceptibility to incidents that can result in considerable reductions in road network serviceability'. This includes a focus of assessment on the most critical hotspots (links or nodes) within a current network system, where the highest socio-economic impact can be observed, which – according to other scholars – equals exposure (Unterrader et al., 2017; Khademi et al., 2015; Jenelius et al., 2006). On

5   the other hand, Taylor et al. (2006) understands network vulnerability as a close concept to network weakness and thus as the consequence of failure to provide sufficient capacity for the 'original' purpose of the system, being, to transfer people and goods from point A to point B. This already shows the close connection of network vulnerability to other terms, such as accessibility, remoteness or robustness, which is linked to the idea of network performance (Yin et al., 2016; Taylor et al., 2006; D'Este and Taylor, 2003). In sum, the idea behind vulnerability is a decline in the 'original' capacity to handle the network flow based

10 on disruption (Yin and Xu, 2010). Nevertheless, in the literature two main directions within network vulnerability assessment can be distinguished: (1) topological vulnerability analysis, which includes the assessment of real transport network systems (represented in an abstract network); and (2) system-based vulnerability analysis, which focuses on the structure of the network within demand/supply models (Mattsson and Jenelius, 2015). In the context of the present study, we understand vulnerability as the assessment of the disruptive impact based on a certain event (incident) which causes a malfunction or breakdown in

15 the current road network system (Postance et al., 2017; Pregnolato et al., 2017; Klose et al., 2015; Mattsson and Jenelius, 2015). The potential disruption may span from natural hazard events to terrorist attacks, infrastructure collapses or ordinary traffic accidents (Bagloee et al., 2017; Unterrader et al., 2017; Vera Valero et al., 2016; Mattsson and Jenelius, 2015; Koetse and Rietveld, 2009; Zischg et al., 2005; Margreth et al., 2003). Depending on the threat, the potential consequence can result in additional travel time from some minutes to total cut-offs of a community (Rupi et al., 2015; Taylor and Susilawati, 2012;

20 Jenelius, 2009; Zischg et al., 2005). Therefore, a central goal of vulnerability assessment is the identification of the critical links within the current network system that are highly susceptible to such disruptions (Bíl et al., 2015; Jenelius et al., 2006; Berdica, 2002). In contrast to the ongoing vulnerability debates in natural hazard management, however, network vulnerability usually does not account for any probability of disruption within the assessment (see for example Papathoma-Köhle et al. (2017); Fuchs et al. (2011) or Fuchs (2009)).

25 Among various causes, the focus of this paper is on landslide hazards, which jeopardize the integrity of land transport systems by causing structural damage and interruptions (Postance et al., 2017; Klose et al., 2015; Bíl et al., 2014). This choice is justified by an estimation of the probability of occurrence based on relative event frequency, by hazard process type. For instance, within 1 444 damaging events to rural roads in the Austrian provinces of Salzburg (2007–2010) and Styria (2008–2011), debris flows and landslides caused nearly 50 % of damage costs, thereby clearly exceeding damages resulting from

30 other events such as windstorms, flooding, or snow avalanches (König et al., 2014b). The prevailing hazard potential caused by landslides is aggravated by the findings of several current studies which have shown that landslide activity and thus related damage will probably increase with progressing climate change (Postance et al., 2017; Bíl et al., 2015; Klose et al., 2015; Strauch et al., 2015; König et al., 2014a). Recent regional hazard events occurring with increasing frequency and severity (at least as far as their impact on transport networks is concerned) seem to be in line with this prediction. Similar results are

available from other mountain regions (e.g. Postance et al., 2017; Unterrader et al., 2017; Meyer et al., 2015; Fuchs et al., 2013).

So far, most studies have mainly focused on primary road networks (i.e. highways, (Postance et al., 2017; Taylor et al., 2006), while federal and local road networks have been largely neglected. Furthermore, mostly issues on technical realization and maintenance have been addressed rather than socio-economic impacts on communities or the society (Mattsson and Jenelius, 2015). Termed as 'forgotten road system', misleadingly, the latter in fact connects rural communities in various ways – from supply reliability over public health and tourism to all sorts of economy. This paper partly closes this gap by assessing the road network vulnerability of alpine communities to landslide events in the context of rural road networks. Mountain roads, in contrast to lowland areas, are highly vulnerable due a higher probability of climate-driven hazard events and the inherent obstacles of implementing redundant systems (Matulla et al., 2017; Schlögl and Matulla, 2017; Schlögl and Laaha, 2017; Doll et al., 2014; Eisenack et al., 2011). Nevertheless, the relation between infrastructure and communal development in mountain areas is not one-directional, meaning that it is only the former that can impact the latter; instead, the influence is rather two-way (Jaafari et al., 2015).

Based on an updated landslide susceptibility map we show the merits of agent-based traffic modeling for gaining insights into the impacts of road network interruptions on the mobility behavior of affected communities. By modeling the responses of individuals to network disturbances the transport model allows for optimizing certain characteristics of agents (e.g. time of departure, route choice, activity list, etc.). Generalized costs of interruptions (i.e. monetary costs, time losses, etc.) are obtainable by employing a utility function to the agents' resulting behavior.

2 Data and methods

Methodologically the approach presented in this paper is divided into two modeling sections:

1. creation of a landslide susceptibility map in order to identify potential blockage sections in the rural road network, and

2. implementation of agent-based transport simulations for deriving impacts of interruptions on local communities.

2.1 Modeling landslide susceptibility

The impact assessment of landslide events on different aspects of society does still pose a great challenge for different groups of stakeholders. In order to evaluate the impacts of the process itself, numerous quantitative methods are in use. Goetz et al. (2015) give a comprehensive overview of different statistical prediction models for the assessment of landslide susceptibility. In this study we use the Weight of Evidence Method (WoE, first presented by Bonham-Carter (1994)) with early application to landslides by Lee et al. (2004). The main concept of WoE is based on the assumption that future landslides are very likely to occur in similar conditions as in the past (Varnes, 1984). This is an important aspect in answering possible effects regarding the occurrence of landslides under a changing climate (Gariano and Guzzetti, 2016). WoE is a data driven method representing a Bayesian approach in a log-linear form. WoE uses a prior and posterior probability for assessing the relations between (i) the

spatial distribution of the areas affected by landslides and (ii) the spatial distribution of the analyzed landslide susceptibility factors also named predictors (van Westen et al., 2008). Consequently, the degree of influence of of each predictor on past and future landslide events can be calculated.

The most decisive database for the statistical modeling of landslide susceptibility is an accurate and representative landslide

5　inventory (Zêzere et al., 2017). Different types of event inventories exist: (i) Historical data from archives, (ii) field mapping results, (iii) information derived from remote sensing data, and (iv) combined inventories (Bell et al., 2012). In general, inventories which are based on archive data do only include events which caused some kind of damage and were reported; landslides occurring in remote areas without significant damages are usually not documented. Event inventories give detailed information about the process type as well as the date and the trigger of the event (e.g. heavy rainfall). In terms of data ac-

10　quisition inventories based on remote sensing data can be distinguished in two groups. Inventories can be derived either from passive optical sensors (products: ortho-images, digital terrain models (DTMs) from photogrammetry) or active sensors (e.g. laserscanning, radar: product: DTMs). Data from passive systems, such as ortho-images, imply the big disadvantage of only sensing the surface from one point per image compared to e.g. laserscanning (constant sensing). Therefore existing vegetation cover often prohibits an area wide, exact mapping of landslides, even in stereoscopic analysis (Petschko et al., 2015). In the

15　last decade the availability of DTMs derived from airborne laserscanning (ALS) offers a new quality of high resolution terrain representation (spatial resolution of 1 m). Penetration of laser pulses give exact 3D-information of the surface – even in areas with high vegetation density – and have thus been used in many studies (Proske and Bauer, 2016; Petschko et al., 2015, 2013a). The most promising approach for the generation of representative event inventories in forested and unforested landscapes, as well as in landscapes which are characterized by intense human activity, proved to be a combination of the analysis of archive

20　data with the visual interpretation of remote sensing data (ALS-data, orthophotos) followed by random field checks (Proske and Bauer, 2016; Guzzetti et al., 2012).

First efforts to delineate geomorphological landforms including mass movements in the study area Vorarlberg date back to the 1950s (Matznetter, 1956). Further approaches include those of Seijmonsbergen (1992); Aulitzky et al. (1994) and van Asselen and Seijmonsbergen (2006). In terms of landslide assessment in the province of Vorarlberg, research activities comprise

25　shallow landslide inventories of elected test site (Zieher et al., 2016) as well as landslide susceptibility analysis of regional test sites (Schmaltz et al., 2016; Ruff and Czurda, 2008).

The government of the province of Vorarlberg offers an official landslide susceptibility map based on a classified geological map and the location of landslides events (details below). In order to generate an enhanced landslide susceptibility map for Vorarlberg (including e.g. an enlarged landslides inventory), we used a routine which was already successfully applied to two

30　other provinces in Austria (Petschko et al., 2013b, 2014; Bell et al., 2013; Klingseisen and Leopold, 2006). Three major data sets constitute the main input for deriving model input parameters as well as for model training and evaluation purposes:

– Historic landslide events ("Rutschungskataster Vorarlberg", points) as model training points;

– Official landslide susceptibility map – including geology – of Vorarlberg ("Gefahrenhinweiskarte", polygons) as a model input parameter;

– DTM of Vorarlberg (5 m grid).

The following list provides an explicit description of parameters used in this study:

– *Inventory of landslide events:* This inventory of landslide events ('Rutschungskataster') is compiled from different data
sources, such as archive data provided by the Austrian Geological Survey ('Geologische Bundesanstalt', GBA), the
Austrian Service for Torrent and Avalanche Control ('Wildbach- und Lawinenverbauung', WLV), the Federal Institute
for Forests ('Bundesamt für Wald', BFW), different provincial staff units, and web data mining. Events are represented
by discrete points within a shapefile with one point for each database entry. The inventory of landslide events includes
information about data source as well as main and differentiated process group (e.g. slides; rock slides). Within this
inventory, information about 1 178 landslides were available.

– *Hazard index map:* The geological map of Vorarlberg (Friebe, 2007) shows 171 different geological units for the entire
province. To obtain suitable input parameters for landslide susceptibility modeling, these units were classified with
respect to their lithological and geotechnical characteristics, generating a hazard index map (HIM). This map presents
four classes representing different levels of geogenic risk roughly representing the main geological units. The polygon
shape file was converted to a 10 m raster image for our modeling purpose. This hazard map offers the only available data
set covering geological information in a rather coarse and highly generalized scale of 1:100 000.

– *Digital terrain model:* The digital terrain model of Vorarlberg represents the data basis for many derivatives which build
main input parameters for the modeling approach. The original DTM raster (derived from airborne laser scanning with a
spatial resolution of 1 m) was already resampled to a 5 m grid and was then again resampled to a 10 m grid in order to be
consistent to the geogenic risk class layer mentioned above. This DTM was used as a basis to derive several additional
input parameters, which are described immediately below.

– *Slope:* The steepness of a hillside certainly is the most obvious factor for slope stability (SLO). The parameter is derived
by selecting as the maximum rate of change in elevation value from a grid cell with respect to its eight neighbors. It is
thus a typical nearest-field parameter, which is expressed as a degree value of slope at the very cell location.

– *Aspect:* While slope gives no information about the geographical direction of the maximum rate of change in elevation,
aspect (ASP) does provide this information with no information about the steepness. The value is calculated as the
angle from north in degrees that features the maximum elevation gradient. Usually, the values are classified in steps of
45°according to the eight compass directions. A ninth class represents flat areas, which are typically defined to comprise
steepness values smaller than 3°. These flat grid cells are commonly excluded in the modeling procedure. It is obvious
that – except for the definition of the last class – the values of slope and aspect are mathematically independent of each
other, only conditioned by the characteristics of the landscape they describe.

– *Positive topographic openness:* Positive Topographic Openness (PTO) characterizes the widest vicinity of a raster cell
(usually radial limits of 10 000 raster cells are used) and expresses the "dominance" of a landscape location, giving an

index of the viewshed size above the horizon line. Hence, higher values represent dominant hilltops, while low values places in narrow valleys. For detailed information see (Yokoyama et al., 2002).

– *Topographic position index:* Topographic Position Index (TPI) compares the elevation of a DTM raster cell to the mean elevation of its neighborhood in a radius of 100 grid cells, that is in our model 1 km. Positive TPI values represent

5　　　　locations that are higher than the average of their surroundings (ridges and hilltops), negative TPI values represent locations that are lower than their surroundings (valleys). TPI values near zero are either flat areas (where the slope is near zero) or areas of constant slope (where the slope of the point is significantly greater than zero). Inherently, the TPR value is highly dependent on the given radius (Guisan et al., 1999).

– *Terrain ruggedness index:* Terrain Ruggedness Index (TRI) was developed by (Riley et al., 1999) to express the amount

10　　　　of elevation difference between adjacent cells of a DTM. It thus characterizes the "smoothness" and the very local structural heterogeneity of a surface.

– *Topographic wetness index:* Topographic Wetness Index (TWI) indicates the local water availability in a cell, based on a precipitation-run off calculation. The size of upslope catchment areas of a cell and the steepness of the slopes are considered in its calculation. As heavy rainfalls are known to be a trigger for shallow landslide events, this parameter

15　　　　is also an important evidence for modelling (Bogaard and Greco, 2018; Martinović et al., 2018; Gariano et al., 2017; Guzzetti et al., 2008; Sørensen et al., 2006).

2.2　Traffic modeling

In order to assess the effects of road network interruptions, an agent-based traffic model was employed in the study area. The underlying data required for setting up a suitable traffic model stems from various sources. In terms of traffic services, open

20　data provided by OpenStreetMap (OpenStreetMap contributors, 2018), by the official road graph of Austria (GIP, 2018) and by the geodata service of the province of Vorarlberg (VoGIS, 2018) were used. The underlying road graph used for the traffic model is based on an OpenStreetMap extract, which was converted into a routeable road graph. Road capacity was derived from the functional road class. In (rare) cases of missing speed data, this information was also derived from the functional road class. Fundamental data concerning traffic demand and agent characterization are based on data provided by Statistics

25　Austria, by the province of Vorarlberg and land use data. This includes data about e.g. traffic behavior of the local population derived from mobility surveys, socio-demographic data such as population numbers, employment statistics, or commuting flows. All of these properties can be used to model and analyze the effects of transport network interruptions on the population in the test region. The agent-based transport model which was set up on these input data was implemented in the multi-agent transport simulation framework MATSim (Horni et al., 2016). This activity-based implementation of the transport model does

30　not only allow for large-scale agent-based transport simulations in the test area, but also retains detailed socio-demographic information on single agents represented in the model runs. The model setup implemented using aforementioned data sources constitutes the representation of traffic flow on a generic, average weekday under normal (i.e. undisturbed) network conditions. This corresponds approximately to the annual average daily traffic (AADT) for on weekdays between Tuesday and Thursday.

Regarding the demographic variable of employment it has to be noted that non-employment is not equivalent to unemployment. Rather, it also includes persons such as pensioners, students and home-makers.

The most significant mode of transport for the predominantly rural areas under investigation is motorized private transport, which mainly consists of cars. As such it is the mode that can be derived best from the available data and therefore is modeled in high detail on the road network. For the other modes with little available data (such as walking or bike), an origin and destination are determined, but no actual tracing of the modeled agents on the network is performed. Instead the agents simply change their position after some time ("teleportation"). For the mode public transport, a trip duration is calculated, again with no explicit simulation of mapping trips onto a transportation network. Due to reasons of relative demand coverage mentioned above, modeling car traffic can be expected to provide a good first-order approximation of the effects of circumstantial changes within the transport network for the investigated area (see section 3.3).

The full mobility simulation comprises several steps, which are facilitated by several software components. There are three main steps in conducting a full model run (Horni et al., 2016):

1. *Definition of the initial demand*: The initial demand arises from the daily activity chains of the population in the test area. It is based on the digital (routeable) road graph, points of interest along the graph and defined sequences of activities of all single agents. These *activity chains* were derived by means of population synthesis (using iterative proportional fitting) based on a mobility survey (Herry et al., 2014), socio-demographic data and land-use information. All activities of each agent are assigned to certain locations and time slots.

2. *Mobility simulation*: The actual mobility simulation is an iterative process carried out by running MATSim with a set of configuration parameters and data. It comprises the three steps of (i) *process simulation*, (ii) *scoring* and (iii) *re-planning*. Each agent features a set of plans with each plan describing the daily activity chain in the form of a desired schedule. Simulating each plan's execution allows determining associated scores, which can be interpreted as econometric utilities. The scoring function used in the simulation is the Charypar-Nagel utility function (Charypar and Nagel, 2005). It evaluates an executed plan by considering late or early arrivals and departures (with opening hours) at facilities, costs of defined and executed activities (e.g. working, shopping, leisure time, education and habitation) and the costs of travel time[1]. Each iteration step an agent selects one plan from its set as the active one to be carried out in simulation. A fraction of all agents are allowed to optimize their score by modifying a plan of their set (e.g. in terms of trip/activity time limits 20 %, route choice 40 %, score improvement 60 %) during the re-planning step. This iterative process is repeated until the average population score stabilizes sufficiently to assume a near-optimal equilibrium.

3. *Output aggregation and analysis*: This final step comprises the aggregation of model results, which are available at a temporal resolution of 1 second in the form of event logs describing the resulting executed plans.

Following the establishment of a user equilibrium in an undisturbed traffic network state as a *baseline-scenario*, the model is re-run on the modified routing graphs for each of the landslide-scenarios considered. For each of these *incident-scenarios*, the

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[1]See Charypar and Nagel (2005) and Horni et al. (2016) for detailed information on the formulation of the Charypar-Nagel scoring function.

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affected network links are removed from the graph in order to indicate a network interruption caused by a landslide, and the altered behaviors of the agents – as displayed by new equilibrium states – are recorded. Consequently, the impact of network disturbances is derived by comparing the new equilibrium state behaviors on the network for any given *incident-scenarios* with the *baseline-scenario*. Generalized costs of interruptions can be obtained from this comparison in terms of e.g. affected agents, travel time or evasion lengths.

For simulation models, a trade-off between accuracy and efficiency has to be considered. Using the full population for all defined incident simulations would result in substantially longer computing times, while yielding only limited benefits in terms of explanatory power. Reduction of the sample sizes in simulation runs is a common workaround, which allows to obtain plausible estimates at reasonable computing times, while the variance of the derived results only slightly increases. Therefore, three different population samples were used for the purposes of this study. These comprise:

1. The total modeled population with roughly 2.6×10^5 persons (*baseline-100*). This population was optimized for 300 iterations to attain a solid equilibrium. It is used as a reference to determine basic properties of the population affected by the landslide incidents. The resulting activity chains were used as the basis for the following two samples.

2. A 10 % random sample drawn from all persons represented in the abovementioned baseline-scenario. It was optimized for 100 additional iterations to ascertain stability after random sampling (*baseline-10*). This sample was mainly used to establish the landslide incidents consequences' evaluation process in a less time-consuming manner, regarding that a percentage of 10 % constitutes the lower threshold recommended for MATSim to obtain consistent results (Balmer et al., 2009).

3. A 30 % random sample drawn from the baseline-scenario, sampled in the same way as the 10 % sample, again with 100 additional stabilizing post-sampling iterations (*baseline-30*). This sample is used to determine the actual consequences of the landslide incidents in a more robust manner, statistically speaking.

To mitigate an underrepresentation of traffic congestion effects, it has to be noted that, with a fractional reduction in the number of agents, the network's attributes in terms of traffic flow and storage capacity have to be reduced, accordingly. For rural roads, with traffic volumes mostly well below maximum capacity, this is not considered to be a major issue.

3   Results

The results section is organized as a description of a dependent process chain presenting (i) the area wide landslide susceptibility map, (ii) blockage points and critical sections in the rural road network, (iii) agent-based transport modeling and (iv) the impacts on the rural network.

3.1   Landslide susceptibility

Visualization of modeling results in terms of a landslide susceptibility map gives a comprehensive picture of potential blockages and critical sections of the rural road network in the province of Vorarlberg (Figure 1). Unfortunately, insufficient quality

of input data hampers the generation of an advanced landslide susceptibility map. While results do not meet our initial expectations, valuable insights can be gained – particularly with respect to subsequent work.
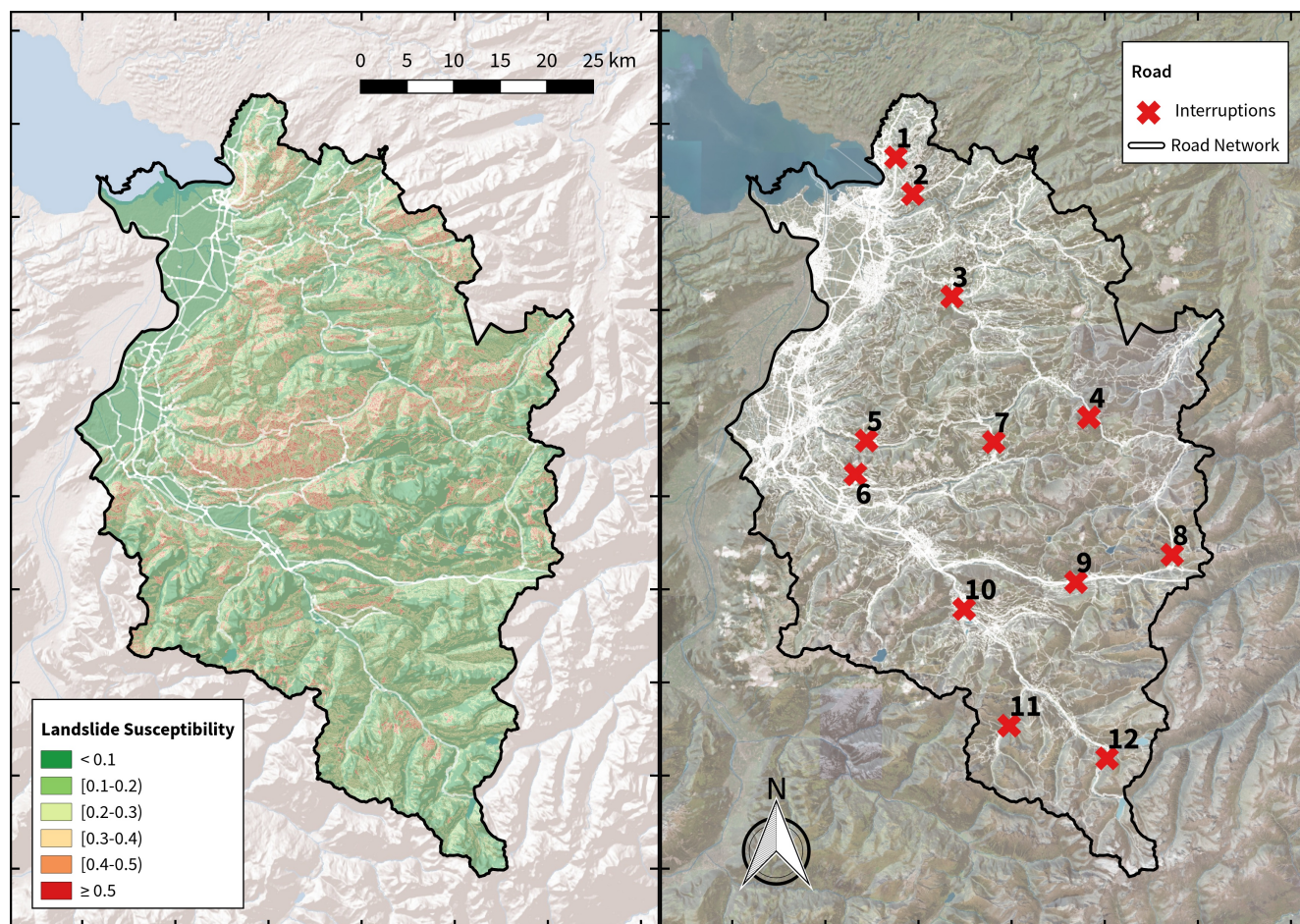

Figure 1. Overview of the study area featuring (a) the updated landslide susceptibility map as well as (b) the road network and the identified critical sections (incident sites).

Basic verification by means of visual interpretation of DTMs and ortho-images rarely shows clear evidence of landslides (Petschko et al., 2015). In the present study, information on landslide localization is given with the differentiation in "exact"

5 and "inexact" without any additional explanation. The description of data acquisition cites literature research (488 events) and archive data available from the Geological Survey of Austria (114 events) as main sources. However sources for several events (116 events) are missing. Acquisition and reporting of events do not seem to be performed in a systematical way; information rather appears to be collected and added to the data set at a certain date. In terms of spatial consistency – which is reflected by conspicuous disparities in data density, which is in turn attributable to different local perception and documentation – landslide

10 events were mapped area wide (e.g. Blons, St. Gerold), in spatial clusters (e.g. Laterns, Fontanella), or even underestimated due

to a lack of sensitization. Hence, districts within the same geological sub-units show significantly different results in landslide reports.

The inventory contains point information about the location of a landslide event with inconsistent information about the position truth. Each landslide event represents a discrete point with no further information about size (cp. polygon delineation).

5 Consequently, larger landslides cover larger areas and landslide areas and are therefore underestimated in the modeling results. An evaluation of the input parameter *position of landslide events* by visually checking the position of landslide points unearthed that in some cases singular landslides are referenced in the inventory through multiple points. Therefore, this overrepresentation of certain events was corrected by filtering this multiple point representation of single landslide to only one point per landslide. Regarding the quality of the localization of landslides in the inventory, several points could not be verified by means of random

10 check using high-resolution orthophotos and a high resolution DTM. This is not solely caused by imprecise localization, but also due to the fact that landslides, which affected traffic routes or (agri-)cultural areas, are usually fixed quickly and efficiently. The modeling routine used needs landslide polygons as input, so we generated a simple 50 m buffer around the inventory points to fulfill this requirement.

The official hazard map of Vorarlberg is based on information available at a scale of 1:100 000, therefore constituting a

15 strongly generalized data basis. Valley bottom sediments are indicated but not consistent with the DTM, and the valley bottom sediments exceed the limits of the foot of slopes. Consequently, the latter influences the information in the geomorphological input parameters such that e.g. the mean slope of the class *valley bottom sediments* is biased.

In order to evaluate the quality of the different input parameters, conditional landslide frequencies within the different categories were assessed. The variables *slope*, *topographic position index* and *terrain ruggedness index* show a nearly normal

20 distribution, whereas the parameters *topographic wetness index* and *positive topographic openness* exhibit a right skewed distribution. Frequencies within the susceptibility classes of the official hazard index map exhibit high count values within the two highest classes 'moderate' (307; 43 %) and 'high' (384; 53 %) – which in fact supports the quality of the official landslide susceptibility hazard classification.

Modeling the weights of evidence yields unexpected results. Approximately 80 % of all landslide events show an occurrence

25 probability of less than 40 % which is considered to be moderate hazard (Neuhaeuser and Terhorst, 2007). These results imply a lower landslide susceptibility than initially expected, eventually effectively underestimating the actual landslide risk. Based on a synthesis of all results, we therefore decided to use both the information from the official hazard map of Vorarlberg and the updated landslide susceptibility map for identifying critical blockage points.

As a side note, it has to be noted that the twelve interruption sections identified in the study area Vorarlberg are unlikely

30 to change considerably with new modeling approaches. The official hazard map already provides a reasonably accurate and consistent basis for the purpose of identifying vulnerable sections.

3.2 Incident sites

By concatenating the results of the landslide susceptibility map with a digital road graph and historic data of landslide inventories, critical sections of the road network were identified (Figure 1). In total, twelve incident sites located in different regions

Table 1. Overview of the weight of evidence models derived for the study area. Maximum landslide susceptibility (WoE$_{max}$) reflects the occurrence probability of landslides within range [0-1]. Input parameters are described in the methods section above. The column 'events' reflects the data sources from the landslide inventory that were used as event data, with 'subset' indicating a reviewed, narrowed and hence more consistent data set

Model	WoE$_{max}$	landslide events	Input Rasters (# of classes)						
			HIM	ASP	SLO	PTO	TPI	TRI	TWI
A	0.50	all	4	–	5	5	5	5	5
B	0.53	subset	4	–	5	5	5	5	5
C	0.64	subset	4	–	10	10	10	10	10
D	0.62	subset	4	9	10	10	10	10	10
E	0.49	subset	–	9	10	10	10	10	10

of the case study area have been selected for further analysis of the impacts of landslide events on the road network (Table 2). Each incident comprises one or multiple links, which were flagged to indicate blockage in case of a landslide event.

Table 2. Overview of the twelve selected incident sites located in landslide-prone areas. The table includes the names of the affected roads, of the geographic region and the toponyms of the affected villages. The average traffic volume is displayed in terms of annual average daily traffic (AADT) and the average daily number of heavy goods vehicles (HGV) on weekdays between Tuesday and Thursday in 2016 [vehicles/day]. In addition, the peak flow per hour (Q$_{max}$) displays the maximum number of vehicles within one hour in 2016. Please note that no traffic counters are available in immediate vicinity for incidents 1 and 11 (Source: VoGIS (2018)).

Incident	Roads	Region	Toponym	ADT$_{2016}$	HGV$_{2016}$	Q$_{max}$
1	L11	Pfänder	Eichenberg	–	–	–
2	L2, L12	Rheintal	Bregenz-Fluh	5171	222	623
3	L48	Bregenzerwald	Andelsbuch	4147	243	973
4	B200	Bregenzerwald	Schoppernau	4331	255	909
5	L51	Laternsertal	Laterns	1472	82	566
6	L73	Walgau	Dünserberg	1693	287	263
7	B193	Großes Walsertal	Fontanella	872	61	428
8	B198	Lechtal	Zürs	3218	346	1048
9	L97, S16	Klostertal	Wald am Arlberg	11702	1716	–
10	B188, L94	Montafon	Bartholomäberg	14860	648	1845
11	L192	Montafon	Gargellen	–	–	–
12	B188	Montafon	Partenen	3217	236	546

A closer look at the transport simulation model revealed that incident 12 had to be removed due to its close proximity to Silvretta-Hochalpenstraße, a high alpine toll road across the Bielerhöhe pass which connects the federal states of Vorarlberg and Tyrol. The combination of an adjacent toll road, complete road-closure during winter months and the incident's proximity to the state-border constitute a rather special traffic pattern, which is difficult to reproduce adequately in a simulation of a much larger area with significantly differing traffic patterns.

3.3 Transport network vulnerability

Transport network model simulations were conducted for the remaining eleven incident sites. For deriving insights from the agent-based transport modelling approach, we focus on the following three main aspects.

First we are interested in the transferability of the traffic model to real world traffic conditions. As the model represents traffic flow on a generic, average weekday with undisturbed network conditions it is reasonable to compare against obtainable measurement data of traffic volumes, where available (VoGIS, 2018). Utilizing the baseline-scenario allows to identify the agents crossing the incident-affected links under normal conditions, as well as their properties. A direct comparison of the annual average daily traffic on weekdays between Tuesday and Thursday (Table 2) with the simulated number of affected car trips (Table 3) shows considerable variability depending on the incidents' location and road-class (e.g. highway, secondary road). While most of the incidents are located in rural areas or at roads with low daily traffic, some of them are very close to (semi-)urban regions or along main roads. Incident 10 is on the main road at the entrance to the Montafon region and therefore an essential part of the road network. This is reflected by the huge number of affected agents and car trips, which are modeled rather fittingly. Incident 11, on the other hand, is at a road segment of a valley's head with few affected agents (Table 3). All incident links providing access to skiing-resorts (e.g. sites 8, 9) can be expected to deviate strongly, as there was no data on tourism-induced traffic available in the mobility survey that served as basis for the traffic model. In some cases the simulation will choose to guide traffic flows on alternate routes (e.g. shift from site 6 to 5 and 7) which are similar with respect to functional road class and travel time. Additional considerations are explored in the discussion below (c.f. section 4.2).

Second we outline the major features of the population affected by each landslide incident's road network obstruction. This also is information gained from analyzing the model's baseline scenario itself. As stated before, Table 3 shows selected incident sites with a broad variability in terms of average daily crossings, ranging from as little as 118 up to more than 16 000 daily car trips. Considering the results of the baseline scenario, both median duration and median distance of daily car trips as well as the share of mode car indicate a strong reliance on this transport mode. Depending on the location of the incident blockage points, about 50 – 80 % of all trips are attributable to working persons. A consistently similar percentage can be found for the employment rate of affected agents, allowing the conclusion of similar stratification regarding the variable of employment, which barely influences the modal share of car-use. The ratio of affected agents to car trips is mostly around 3.5. Cases 9 and 11, which are difficult to model appropriately due to reasons mentioned before, show strong deviations. According to the medians of baseline results, which are used as robust indicators for comparing distributions, non-employed persons complete longer daily trips with respect to both distance and time.

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Table 3. Summary of car trip characteristics for agents in the traffic model of the undisturbed baseline scenario, to be affected by incident scenarios. Affected agents refer to those crossing the incident site at least once, within their regular daily plans. Employment rate is the share of working people within this group. Affected car trips designate the number of incident site traversals by those agents in that transport mode. The share of mode car gives the proportion of site traversals by car relative to all traversals mentioned before (in any mode). Site traversals of incident links by car undertaken by employed people are shown as percentage in column six. Medians of daily travel time and distance are displayed for employed and not employed people, respectively, which again refer to all affected agents and their trips crossing the respective site.

Incident	affected agents []	employment rate [%]	affected car trips []	share of mode car $\widehat{=}$ [%]	car trips by employed [%]	median daily travel time [h:m:s]		median daily travel distance [km]	
						employed	not employed	employed	not employed
1	565	83.54	1363	93.81	82.17	00:46:58	00:51:13	46.4	54.9
2	1486	64.20	3968	91.66	63.38	01:01:02	01:12:18	62.5	76.4
3	4794	64.15	13856	93.15	62.12	01:31:14	01:43:30	91.5	106.3
4	586	58.42	4285	93.33	56.24	02:07:49	02:22:19	118.2	143.5
5	858	67.53	3032	95.74	63.36	01:18:40	01:47:11	79.3	110.9
6	128	73.19	355	89.65	71.27	00:53:31	01:06:54	58.3	68.9
7	572	63.68	3200	93.73	60.81	01:52:53	01:59:40	103.2	118.8
8	1404	49.68	6305	92.93	49.72	02:13:48	02:18:50	159.4	166.8
9	576	52.06	7815	92.07	51.63	02:01:21	02:12:20	149.1	160.6
10	4709	52.16	16372	91.87	51.62	01:24:32	01:32:02	104.4	122.1
11	5	74.00	118	87.41	75.42	01:14:50	02:08:56	75.2	156.5

As a third aspect, we are interested in the differential changes in travel patterns within the model. They can be analyzed by comparing the newly established traffic equilibria, which result from the interruptions occurring at the defined incident sites, against the baseline situation. In some situations the blockage of a non-redundant link can occur, meaning that no alternative routes are available, as is the case for incident 11. Here, it is of no benefit to run a traffic simulation on the modified road

5   graph affected by the landslide event. All agents striving to cross the incident site would simply be marooned in a valley or be unable to reach it by car from the outside, respectively. Results for all other incidents show a broad range of possible scenarios (see Table 4) that might occur in case of network interruptions. The *detour length*, being the shortest alternate route length between the ends of the road links that were severed by the landslide, ranges from around 3 km up to 108 km. This distance is not necessarily reflected in the *evasion lengths* of actual car trips made in the simulation, because agents learn

10   to give these interruptions an adequately wide berth, still striving to optimize their score. While optimized circumnavigation results in an increase of travel time across the board (*evasion time* > 0), our findings show that travel distance might actually decrease in some cases (*evasion length* < 0). This is attributable to the choice of lower priority alternate routes with smaller effective capacities (due to road-class and/or congestion) resulting in lower traveling speeds, yet shorter lengths. The quartiles were chosen to convey an impression of the distributions underlying the aggregated evasion quantities. Given the geographic

15   situation in Vorarlberg, which is characterized by narrow valleys and mountains that serve as natural barriers, the closing of

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Table 4. Summary statistics of differences between each interruption scenario and the undisturbed baseline scenario, for both (10 % and 30 %) population samples. They are expressed in terms of quartiles of (additional) evasion lengths and times. For incident site 10, two individual stretches of road are affected (NE/SW), therefore two different detour lengths are indicated.

| Incident | detour length [km] | incident scenarios: 10 % sample | | | | | | incident scenarios: 30 % sample | | | | | |
| | | evasion time [h:m:s] | | | evasion length [km] | | | evasion time [h:m:s] | | | evasion length [km] | | |
		q_{25}	q_{50}	q_{75}	q_{25}	q_{50}	q_{75}	q_{25}	q_{50}	q_{75}	q_{25}	q_{50}	q_{75}
1	16.4	00:05:41	00:12:10	00:22:34	5.04	8.18	13.01	00:08:07	00:12:02	00:23:34	6.27	8.94	17.01
2	50.2	00:14:47	00:31:48	00:52:06	14.71	21.80	46.10	00:15:53	00:25:14	00:44:55	12.00	20.92	38.81
3	11.9	00:04:05	00:07:02	00:10:21	7.28	9.79	17.06	00:03:20	00:06:15	00:08:53	7.19	9.57	17.30
4	106.9	00:06:32	00:16:11	00:44:30	37.85	61.17	72.97	00:09:23	00:19:43	00:52:20	39.47	66.26	86.44
5	65.7	00:12:51	00:16:10	00:49:54	7.63	19.88	34.52	00:10:58	00:24:44	00:51:10	11.09	22.90	45.14
6	27.2	00:07:56	00:10:36	00:11:25	11.90	15.17	15.89	00:04:20	00:05:43	00:11:20	7.11	8.28	15.21
7	65.7	00:06:24	00:13:22	00:21:22	18.32	27.39	46.30	00:06:52	00:11:52	00:21:32	18.61	32.58	48.13
8	107.9	00:10:42	00:21:18	00:34:51	-30.52	-15.82	8.61	00:13:09	00:27:58	00:42:52	-22.90	-5.38	16.51
9	107.7	00:15:05	00:31:50	01:14:09	-21.62	-0.71	31.43	00:17:15	00:35:56	01:15:42	-17.98	3.64	37.22
10	9.6 / 2.6	00:02:38	00:04:01	00:05:31	0.79	1.42	1.79	00:02:30	00:03:10	00:04:16	0.84	1.68	1.77

specific road segments often results in a dramatic increase of travel distances. This is illustrated by the examples of incidents 4, 8 and 9 where detour length exceeds 100 km as there are no parallel routes traversable at comparable utility score in the used road network model.

    Figure 2 shows relative evasion quantities, which are obtained by comparing the daily aggregates of every agent's trips for each incident scenario against their counterparts in the baseline scenario. A summary over all affected agents across all incident scenarios and both travel time and distance shows the median of relative quantities to increase by approximately 7 %. Results show that up to two times the amount of initial travel time and distance is required for evading a majority of the modeled incidents. In some outlier cases, up to the sevenfold time and distance is spent making the agents' daily journeys by car. However, on exceptionally rare occasions (i.e. 3 out of 5 518 agents in the 30 % sample) it can also be observed that daily travel time and distance decrease marginally ($\approx -0.2\,\%$) relative to the baseline scenario. This seemingly paradoxical phenomenon is explored further in the discussion. An obvious feature when comparing the employment status are the wider tails in the distributions of evasion costs for employed drivers, as indicated by taller boxes and longer whiskers. This attributable to peak traffic conditions resulting in wider detour variations.

4 Discussion

4.1 Landslide modeling

Our efforts to refine the official landslide susceptibility map of Vorarlberg by using additional input data in a WoE approach revealed some substantial shortcomings in the data basis. The quality of the distribution of the recorded events in the landslide
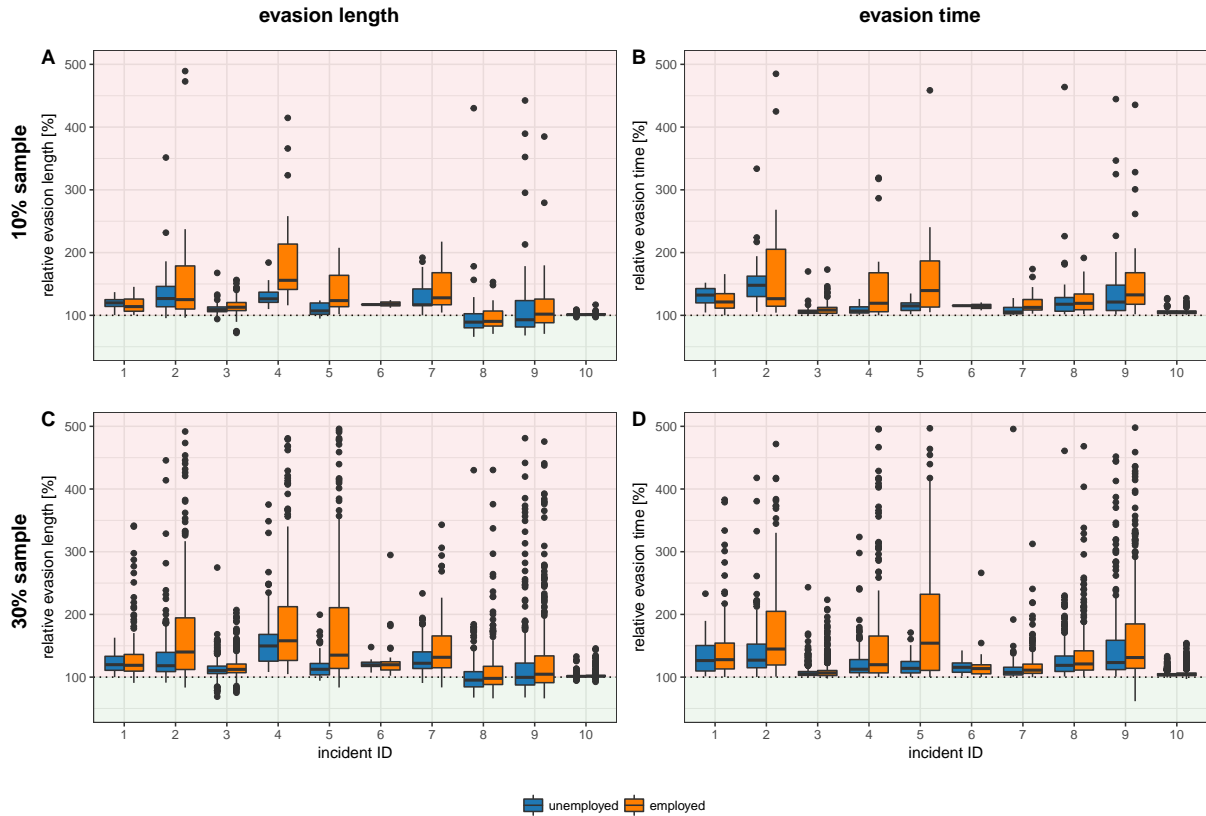
Figure 2. Relative changes of evasion length and evasion time with respect to the baseline scenario resulting from landslide-induced network impairment. Boxplots in the upper / lower row show results for the 10 / 30 % sample, respectively. A discrimination of evasion costs between employed and non-employed agents is color-coded. Note that the y-axis has been limited at 500 % for better readability. Occasional outliers exist up to 700 %.

inventory appears to be a major impediment for obtaining an enhanced susceptibility map. In order to achieve a satisfying result, an area-wide mapping of landslides (points and/or polygons of extent based on ALS high resolution DTMs) is considered to be a crucial data base for modeling purposes (Zieher et al., 2016; Petschko et al., 2013b). Furthermore, there is a demand for (i) an area wide objective assessment and mapping as well as reporting of landslide events, including a subsequent addition of these events into the landslide inventory, and (ii) consistent information about meta-data.

The quality of the geological map – which is another major input factor for modeling landslide susceptibility – forms another obstacle. The area-wide map used in has a scale of 1:100 000 and is thus is highly generalized, therefore providing rather coarse information. Geological maps in a scale of 1:50 000 are only available in small parts of the province of Vorarlberg. Moreover the official hazard map is mainly oriented on the main geological units, e.g. alluvial depositions in the valley bottom are not depicted exactly, therefore the geohazard information shows some uncertainties. Both an accurate landslide inventory and

precise geological information at a high spatial resolution will substantially support the modeling approach, whose applicability and added value over coarse susceptibility maps was already successfully shown for other provinces of Austria, such as Lower Austria (Petschko et al., 2014), Styria (Proske and Bauer, 2016) and Burgenland (Leopold et al., 2017).

4.2 Traffic impact assessment

5   Regarding the application of an agent-based traffic model for assessing the impacts of landslide-triggered road network interruptions in a rural alpine area, our findings comprise several notable aspects.

Generally speaking, medians of total daily car travel times and distances appear to be rather long (Table 2). Considering the background of spatial planning and topographical structure in the area shows that this is nothing out of the ordinary. Agglomerations and activity centers are mainly located either in the Rhine valley or its tributary valley, the Walgau, which
10   entails long driving routes for commuters in remote areas.

It also can be observed that total daily trips of employed agents are shorter than those of the non-employed – as far as both daily travel time and daily travel distance are concerned (Table 2). This is explained by the daily schedules of the non-employed agents who fulfill various chores which shows in the consistently smaller percentage of car trips by employed agents compared to the employment rate. The occasional extra car-trip by non-employed agents covers the daily travel differences of $\approx 5-10\,\%$.

15   Concerning evasion effects as shown in Table 3, it is interesting to note that evasion times are sometimes surprising when paired with the corresponding quartile of evasion length. Here it has to be noted that a small increase in travel time can still be accompanied by a longer increase in travel distance, given the choice of an appropriate high speed (and capacity) road. For incidents with shorter detour length (Table 3) the inter-quartile range ($q_{75} - q_{25}$) of evasion times tends to be reduced in the $30\,\%$ sample when compared to the $10\,\%$ sample, while for the incidents with long detours (i.e. incident 4, 8 and 9) there is an
20   opposite tendency. The source of these small effects is yet to be explored in detail, but it most likely is due to the greater number of agents required to spread out over a wider area of the network, thus causing network loading effects in the simulation which are not fully compensated by the population-equivalent scaling of road capacities.

Our results indicate that employed agents in general are more affected by network interruptions, for the medians of relative evasion costs being mostly higher (Figure 2). As it is the case with the aforementioned wider-tailed distributions of evasion
25   cost for employed agents, this most likely stems from stricter time constraints in terms of working hours, entailing that the employed agents are more prone to congestion effects caused by rush hour traffic peaks.

A somewhat paradoxical situation emerges at incidents 8 and 9, where results show negative evasion lengths compared to the baseline scenario. Such effects likely occur when it becomes necessary to use roads featuring a lower functional road class (which feature lower speed limits, or at least lower effective speeds) than in the baseline scenario, thus entailing shorter travel
30   distances but longer travel times. For instance, instead of using the highway S16 to cross incident link 9, agents have to use rural roads between the two corresponding highway junctions, which can lead to a decrease in travel distance at the expense of a corresponding increase in travel time.

Even though evasion times show consistent overall increases, there are sporadic cases where both travel time and distance decrease when contrasted to the baseline scenario. It has to be noted, however, that these cases are extremely rare and well

within a realistic scenario. The establishment of a new user-equilibrium on the road network can – for very few agents – sometimes result in better individual outcomes under worse overall circumstances.

It can be observed that the models for the disturbed situations show shifts in agent trip start and end time. This indicates that agents naturally learn to e.g. adjust their departure time to reach their offices in time. However, no general patterns can be derived from these observations, as these adjustments vary strongly between single agents.

However, results have to be interpreted under consideration of several limitations. It has to be noted that the points of interest within the daily plans of agents are static. Consequently, the re-planning procedure so far does not include re-assignment to substitute facilities. This may not appropriately reflect reality since it is very likely that – in case of activities where alternative facilities exist – people would adjust their evasion routes accordingly. They would, for example, do their grocery shopping at a different and more accessible supermarket location.

Despite the quantitative similarity of the traffic simulation to actual traffic measurements of an investigated area might always be improved upon (which often is the case for comparable mathematically ill-defined problems), its informative value can still be derived from a comparative analysis as demonstrated in this work.

In the case of the employed traffic model, the reasons for deviations from traffic measurement data are the following. Firstly, our model only considers trips by inhabitants of Vorarlberg. Consequentially, cross-border traffic from both people commuting from outside (e.g. Tyrol, Germany, Switzerland) to Vorarlberg as well as transit through Austria are not taken into consideration. While this restriction has less effects in rural areas in the alpine region (where many of the considered incidents are located), effects will get more pronounced in areas next to a border or on highways with high volumes of transit (see Table 2). Secondly, distortions may arise due to an unavoidable temporal mis-alignment of utilized data sources. While the underlying mobility household survey that serves as basis for the MATsim model was conducted in 2013 (Herry et al., 2014), the available traffic counts refer to the year 2016.

5   Conclusions

This study examined the different impacts of landslide-induced road network interruptions on communities in a rural area in the European Alps. In general, road network systems are highly complex – most notably regarding their socio-economic effects on communities. Alpine areas are particularly vulnerable to such interruptions and changes. Firstly, this is based on their topography. Mountain regions are usually prone towards natural hazards events, often lacking the feasibility to build a redundant transport system. Secondly, because of their socio-economic properties, mountain regions are strongly dependent on the established road network (i.e. dependency on tourism and high numbers of commuters). This implicates a political debate on the question of how to manage mountain road network systems.

Despite several limitations, the efforts undertaken in this study can offer valuable guidance for decision makers, by providing a sound estimation of likely implications of landslide-triggered road network interruptions on local communities. In particular, information on the number of affected people, their employment status as well as their associated costs (in terms of both time loss and evasion length) can serve as a basis for gauging possible adaptation and protection measures in a broader context.

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Additionally, such findings can contribute to decision making by prioritizing such measures in line with budgetary constraints. Supplying decision support on where and how to efficiently and effectively allocate limited resources is beneficial for the whole society. It enables tackling the impacts of adverse weather events and natural hazards by means of appropriate measures.

In this paper we have shown that agent-based traffic modeling allows to gain interesting insights into the impacts of road
5 network interruptions on the mobility behavior of affected communities by modeling their responses to network disturbances. The detailed representation of single agents in the transport model allows for optimizing certain characteristics of agents (e.g. time of departure, route choice, activity list, etc.). Generalized costs of interruptions (i.e. monetary costs, time losses, etc.) can be obtained by employing a utility function to the agents' resulting behavior. Therefore, the MATSim implementation is considered to be particularly suitable for providing a agent-based analysis of expected impacts on changes in the traffic system.
10 Our findings are meant to provide a basis for future work in this area, which should expand the limits of the present study by incorporating transit and cross-border traffic and might shed more light on traffic displacement effects. Moreover, further work could be devoted to the economic analysis of interruption costs.

While this study has explored road network vulnerability against the background of landslide susceptibility, the presented methodology is easily transferable to other (natural) hazards that might cause network interruptions, such as e.g. avalanches,
15 floods, or terrorist attacks.

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References

Aulitzky, H., Heuberger, H., and Patzelt, G.: Mountain Hazard Geomorphology of Tyrol and Vorarlberg, Austria, Mountain Research and Development, 14, 273–305, https://doi.org/10.2307/3673725, 1994.

Bagloee, S. A., Sarvi, M., Wolshon, B., and Dixit, V.: Identifying critical disruption scenarios and a global robustness index tailored to real life road networks, Transportation Research Part E: Logistics and Transportation Review, 98, 60–81, https://doi.org/10.1016/j.tre.2016.12.003, 2017.

Balmer, M., Rieser, M., Meister, K., Charypar, D., Lefebvre, N., Nagel, K., and Axhausen, K.: MATSim-T: Architecture and Simulation Times, in: Multi-Agent Systems for Traffic and Transportation Engineering, edited by Bazzan, A. L. C. and Klügl, F., p. 57–78, https://doi.org/10.4018/978-1-60566-226-8.ch003, 2009.

Bell, R., Röhrs, H. P. M., and Dix, A.: Assessment of landslide age, landslide persistence and human impact using airborne laser scanning digital terrain models, Geografiska Annaler: Series A, Physical Geography, 94, 135–156, https://doi.org/10.1111/j.1468-0459.2012.00454.x, 2012.

Bell, R., Glade, T., Granica, K., Heiss, G., Leopold, P., Petschko, H., Pomaroli, G., Proske, H., and Schweigl, J.: Landslide Susceptibility Maps for Spatial Planning in Lower Austria, in: Landslide Science and Practice: Volume 1: Landslide Inventory and Susceptibility and Hazard Zoning, edited by Margottini, C., Canuti, P., and Sassa, K., pp. 467–472, Springer Berlin Heidelberg, Berlin, Heidelberg, https://doi.org/10.1007/978-3-642-31325-7_60, 2013.

Berdica, K.: An introduction to road vulnerability: what has been done, is done and should be done, Transport Policy, 9, 117–127, https://doi.org/10.1016/S0967-070X(02)00011-2, 2002.

Bíl, M., Kubeček, J., and Andrášik, R.: An epidemiological approach to determining the risk of road damage due to landslides, Natural Hazards, 73, 1323–1335, https://doi.org/10.1007/s11069-014-1141-4, 2014.

Bíl, M., Vodák, R., Kubeček, J., Bílová, M., and Sedoník, J.: Evaluating road network damage caused by natural disasters in the Czech Republic between 1997 and 2010, Transportation Research Part A: Policy and Practice, 80, 90–103, https://doi.org/10.1016/j.tra.2015.07.006, 2015.

Bíl, M., Andrášik, R., Nezval, V., and Bílová, M.: Identifying locations along railway networks with the highest tree fall hazard, Applied Geography, 87, 45–53, https://doi.org/10.1016/j.apgeog.2017.07.012, 2017.

Bogaard, T. and Greco, R.: Invited perspectives: Hydrological perspectives on precipitation intensity-duration thresholds for landslide initiation: proposing hydro-meteorological thresholds, Natural Hazards and Earth System Sciences, 18, 31–39, https://doi.org/10.5194/nhess-18-31-2018, 2018.

Bonham-Carter, G. F.: Geographic Information Systems for Geoscientists: Modelling with GIS, vol. 13 of *Computer Methods in Geosciences*, Pergamon, 1994.

Charypar, D. and Nagel, K.: Generating complete all-day activity plans with genetic algorithms, Transportation, 32, 369–397, https://doi.org/10.1007/s11116-004-8287-y, 2005.

D'Este, G. M. and Taylor, M. A. P.: Network Vulnerability: An Approach to Reliability Analysis at the Level of National Strategic Transport Networks, in: The Network Reliability of Transport, edited by Bell, M. G. H. and Iida, Y., pp. 23–44, https://doi.org/10.1108/9781786359544-002, 2003.

Doll, C., Trinks, C., Sedlacek, N., Pelikan, V., Comes, T., and Schultmann, F.: Adapting rail and road networks to weather extremes: case studies for southern Germany and Austria, Natural Hazards, 72, 63–85, https://doi.org/10.1007/s11069-013-0969-3, 2014.

Donnini, M., Napolitano, E., Salvati, P., Ardizzone, F., Bucci, F., Fiorucci, F., Santangelo, M., Cardinali, M., and Guzzetti, F.: Impact of event landslides on road networks: a statistical analysis of two Italian case studies, Landslides, 14, 1521–1535, https://doi.org/10.1007/s10346-017-0829-4, 2017.

eHORA: Natural Hazard Overview & Risk Assessment Austria, http://www.hora.gv.at/, accessed: 2018-03-13, 2018.

5 Eidsvig, U. M. K., Kristensen, K., and Vangelsten, B. V.: Assessing the risk posed by natural hazards to infrastructures, Natural Hazards and Earth System Sciences, 17, 481–504, https://doi.org/10.5194/nhess-17-481-2017, 2017.

Eisenack, K., Stecker, R., Reckien, D., and Hoffmann, E.: Adaptation to Climate Change in the Transport Sector: A Review, pIK-Report, 122, Potsdam, 2011.

European Commission: EU transport in figures – statistical pocketbook 2017, https://doi.org/10.2832/041248, https://ec.europa.eu/transport/
10 sites/transport/files/pocketbook2017.pdf, 2017.

Friebe, J. G.: Geologie der österreichischen Bundesländer – VORARLBERG, 2007.

Fuchs, S.: Susceptibility versus resilience to mountain hazards in Austria - paradigms of vulnerability revisited, Natural Hazards and Earth System Sciences, 9, 337–352, https://doi.org/10.5194/nhess-9-337-2009, 2009.

Fuchs, S., Kuhlicke, C., and Meyer, V.: Editorial for the special issue: vulnerability to natural hazards–the challenge of integration, Natural
15 Hazards, 58, 609–619, https://doi.org/10.1007/s11069-011-9825-5, 2011.

Fuchs, S., Keiler, M., Sokratov, S., and Shnyparkov, A.: Spatiotemporal dynamics: the need for an innovative approach in mountain hazard risk management, Natural Hazards, 68, 1217–1241, https://doi.org/10.1007/s11069-012-0508-7, 2013.

Gariano, S., Rianna, G., Petrucci, O., and Guzzetti, F.: Assessing future changes in the occurrence of rainfall-induced landslides at a regional scale, Science of The Total Environment, 596, 417–426, https://doi.org/10.1016/j.scitotenv.2017.03.103, 2017.

20 Gariano, S. L. and Guzzetti, F.: Landslides in a changing climate, Earth-Science Reviews, 162, 227–252, https://doi.org/10.1016/j.earscirev.2016.08.011, 2016.

GIP: Graph Integration Platform Austria, http://gip.gv.at/home-en.html, accessed: 2018-03-13, 2018.

Goetz, J., Brenning, A., Petschko, H., and Leopold, P.: Evaluating machine learning and statistical prediction techniques for landslide susceptibility modeling, Computers & Geosciences, 81, 1–11, https://doi.org/10.1016/j.cageo.2015.04.007, 2015.

25 Guisan, A., Weiss, S., and Weiss, A.: GLM versus CCA spatial modeling of plant species distribution, Plant Ecology, 143, 107–122, https://doi.org/10.1023/A:1009841519580, 1999.

Gutiérrez, J. and Urbano, P.: Accessibility in the European Union: the impact of the trans-European road network, Journal of Transport Geography, 4, 15–25, https://doi.org/10.1016/0966-6923(95)00042-9, 1996.

Guzzetti, F., Peruccacci, S., Rossi, M., and Stark, C. P.: The rainfall intensity–duration control of shallow landslides and debris flows: an
30 update, Landslides, 5, 3–17, https://doi.org/10.1007/s10346-007-0112-1, 2008.

Guzzetti, F., Mondini, A. C., Cardinali, M., Fiorucci, F., Santangelo, M., and Chang, K.-T.: Landslide inventory maps: New tools for an old problem, Earth-Science Reviews, 112, 42–66, https://doi.org/10.1016/j.envsoft.2017.06.042, 2012.

Herry, M., Tomschy, R., and Steinacher, I.: Mobilitätserhebung Vorarlberg 2013. Eckdaten der Befragung, Einstellungen und Meinungen, https://www.vorarlberg.at/pdf/verkehrsbefragungkontiv20.pdf, 2014.

35 Horni, A., Nagel, K., and Axhausen, K. W.: Multi-Agent Transport Simulation MATSim, https://doi.org/10.5334/baw, 2016.

Jaafari, A., Najafi, A., Rezaeian, J., Sattarian, A., and Ghajar, I.: Planning road networks in landslide-prone areas: A case study from the northern forests of Iran, Land Use Policy, 47, 198–208, https://doi.org/10.1016/j.landusepol.2015.04.010, 2015.

Natural Hazards
and Earth System
Sciences
Discussions

Jaiswal, P., Westen, C. J. v., and Jetten, V.: Quantitative assessment of direct and indirect landslide risk along transportation lines in southern India, Natural Hazards and Earth System Sciences, 10, 1253–1267, https://doi.org/10.5194/nhess-10-1253-2010, 2010.

Jenelius, E.: Network structure and travel patterns: explaining the geographical disparities of road network vulnerability, Journal of Transport Geography, 17, 234–244, https://doi.org/10.1016/j.jtrangeo.2008.06.002, 2009.

5   Jenelius, E., Petersen, T., and Mattsson, L.-G.: Importance and exposure in road network vulnerability analysis, Transportation Research Part A: Policy and Practice, 40, 537–560, https://doi.org/10.1016/j.tra.2005.11.003, 2006.

Kappes, M. S., Keiler, M., von Elverfeldt, K., and Glade, T.: Challenges of analyzing multi-hazard risk: a review, Natural Hazards, 64, 1925–1958, https://doi.org/10.1007/s11069-012-0294-2, 2012.

Keller, S. and Atzl, A.: Mapping Natural Hazard Impacts on Road Infrastructure – The Extreme Precipitation in Baden-Württemberg, 10   Germany, June 2013, International Journal of Disaster Risk Science, 5, 227–241, https://doi.org/10.1007/s13753-014-0026-1, 2014.

Kellermann, P., Schöbel, A., Kundela, G., and Thieken, A. H.: Estimating flood damage to railway infrastructure – the case study of the March River flood in 2006 at the Austrian Northern Railway, Natural Hazards and Earth System Sciences, 15, 2485–2496, https://doi.org/10.5194/nhess-15-2485-2015, 2015.

Khademi, N., Balaei, B., Shahri, M., Mirzaei, M., Sarrafi, B., Zahabiun, M., and Mohaymany, A. S.: Transportation network vul- 15   nerability analysis for the case of a catastrophic earthquake, International Journal of Disaster Risk Reduction, 12, 234–254, https://doi.org/10.1016/j.ijdrr.2015.01.009, 2015.

Klingseisen, B. and Leopold, P.: Landslide Hazard Mapping in Austria, GIM International, 20, 41–43, 2006.

Klose, M., Damm, B., and Terhorst, B.: Landslide cost modeling for transportation infrastructures: a methodological approach, Landslides, 12, 321–334, https://doi.org/10.1007/s10346-014-0481-1, 2015.

20   Koetse, M. J. and Rietveld, P.: The impact of climate change and weather on transport: An overview of empirical findings, Transportation Research Part D: Transport and Environment, 14, 205–221, https://doi.org/10.1016/j.trd.2008.12.004, 2009.

König, M., Loibl, W., and Steiger, R.: Climate Change Impacts on the Anthroposphere, in: Austrian Assessment Report 2014 (AAR14), edited by on Climate Change (APCC), A. P., pp. 641–704, Austrian Academy of Sciences Press, Vienna, Austria, 2014a.

König, M., Wolkinger, B., Bednar-Friedl, B., and Felderer, A.: Ein Anpassungsfahrplan für die österreichische Straßenverkehrsinfrastruktur, 25   Vienna, Austria, REP-0495, 2014b.

Lee, S., Choi, J., and Min, K.: Probabilistic landslide hazard mapping using GIS and remote sensing data at Boun, Korea, International Journal of Remote Sensing, 25, 2037–2052, https://doi.org/10.1080/01431160310001618734, 2004.

Leopold, P., Avian, M., and Heiss, G.: Forschungsprojekt Massenbewegungen in den Bezirken Jennersdorf und Güssing: Neubearbeitung der Gefahren-Hinweiskarte sowie Empfehlungen zur Flächenwidmung, Forschungsbericht – Landesregierung Burgenland, pp. 1–46, 2017.

30   Margreth, S., Stoffel, L., and Wilhelm, C.: Winter opening of high alpine pass roads – analysis and case studies from the Swiss Alps, Cold Regions Science and Technology, 37, 467–482, https://doi.org/10.1016/S0165-232X(03)00085-5, iSSW 2002: International Snow Science Workshop, 2003.

Martinović, K., Gavin, K., Reale, C., and Mangan, C.: Rainfall thresholds as a landslide indicator for engineered slopes on the Irish Rail network, Geomorphology, 306, 40–50, https://doi.org/10.1016/j.geomorph.2018.01.006, 2018.

35   Mattsson, L.-G. and Jenelius, E.: Vulnerability and resilience of transport systems – A discussion of recent research, Transportation Research Part A: Policy and Practice, 81, 16 – 34, https://doi.org/10.1016/j.tra.2015.06.002, resilience of Networks, 2015.

Matulla, C., Hollósi, B., Andre, K., Gringinger, J., Chimani, B., Namyslo, J., Fuchs, T., Auerbach, M., Herrmann, C., Sladek, B., Berghold, H., Gschier, R., and Eichinger-Vill, E.: Climate Change driven evolution of hazards to Europe's transport infrastructure throughout the twenty-first century, Theoretical and Applied Climatology, https://doi.org/10.1007/s00704-017-2127-4, 2017.

Matznetter, K.: Der Vorgang der Massenbewegung an Beispielen des Klostertales in Vorarlberg, geographischer Jahresbericht aus Österreich,
5   XXVI. Bd. (1955–1956), 1956.

Mejuto, D. G.: A Europe of multiple flows: Contested discursive integration in trans-European transport infrastructure policy-making, European Urban and Regional Studies, 24, 425–441, https://doi.org/10.1177/0969776416663809, 2017.

Meyer, N. K., Schwanghart, W., Korup, O., and Nadim, F.: Roads at risk: traffic detours from debris flows in southern Norway, Natural Hazards and Earth System Sciences, 15, 985–995, https://doi.org/10.5194/nhess-15-985-2015, 2015.

10   Meyer, V., Becker, N., Markantonis, V., Schwarze, R., van den Bergh, J. C. J. M., Bouwer, L. M., Bubeck, P., Ciavola, P., Genovese, E., Green, C., Hallegatte, S., Kreibich, H., Lequeux, Q., Logar, I., Papyrakis, E., Pfurtscheller, C., Poussin, J., Przyluski, V., Thieken, A. H., and Viavattene, C.: Review article: Assessing the costs of natural hazards – state of the art and knowledge gaps, Natural Hazards and Earth System Sciences, 13, 1351–1373, https://doi.org/10.5194/nhess-13-1351-2013, 2013.

Nemry, F. and Demirel, H.: Impacts of Climate Change on Transport: A focus on road and rail transport infrastructures, 2012.

15   Neuhaeuser, B. and Terhorst, B.: Landslide susceptibility assessment using "weights-of-evidence" applied to a study area at the Jurassic escarpment (SW-Germany), Geomorphology, 86, 12–24, https://doi.org/10.1016/j.envsoft.2017.06.042, 2007.

NZZ: Das durch einen Felssturz abgeschnittene Tal in Österreich ist provisorisch wieder erreichbar, https://www.nzz.ch/panorama/felsmassen-verschuetten-strasse-in-oesterreich-bis-zu-50-meter-hoch-ld.1342688, accessed: 2018-02-27, 2018.

OpenStreetMap contributors: OSM planet dump for Europe, sub region Austria, https://download.geofabrik.de/europe.html, accessed: 2018-
20   03-13, 2018.

ORF: Zwei Felsstürze behindern Verkehr am Reschen, http://tirol.orf.at/news/stories/2887932/, accessed: 2018-02-27, 2018a.

ORF: Kritische Situation im Westen, http://orf.at/stories/2421208/2421209/, accessed: 2018-02-27, 2018b.

Pachauri, R. and Meyer, L., eds.: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, 2014.

25   Papathoma-Köhle, M., Gems, B., Sturm, M., and Fuchs, S.: Matrices, curves and indicators: A review of approaches to assess physical vulnerability to debris flows, Earth-Science Reviews, 171, 272–288, https://doi.org/10.1016/j.earscirev.2017.06.007, 2017.

Petschko, H., Bell, R., and Glade, T.: Landslide inventories for reliable susceptibility maps, Landslide Science and Practice, 1, 281–286, https://doi.org/10.1007/978-3-642-31325-7_37, 2013a.

Petschko, H., Bell, R., Leopold, P., Heiss, G., and Glade, T.: Landslide Inventories for Reliable Susceptibility Maps in Lower Austria, in:
30   Landslide Science and Practice: Volume 1: Landslide Inventory and Susceptibility and Hazard Zoning, edited by Margottini, C., Canuti, P., and Sassa, K., pp. 281–286, Springer Berlin Heidelberg, Berlin, Heidelberg, https://doi.org/10.1007/978-3-642-31325-7_37, 2013b.

Petschko, H., Brenning, A., Bell, R., Goetz, J., and Glade, T.: Assessing the quality of landslide susceptibility maps - Case study Lower Austria, Natural hazards and earth system sciences, 14, 95–118, https://doi.org/10.5194/nhess-14-95-2014, 2014.

Petschko, H., Bell, R., Leopold, P., Heiss, G., and Glade, T.: Effectiveness of visually analyzing LiDAR DTM derivatives for earth and
35   debris slide inventory mapping for statistical susceptibility modeling, Landslides, 13, 857–872, https://doi.org/10.1007/s10346-015-0622-1, 2015.

Pfurtscheller, C.: Regional economic impacts of natural hazards – the case of the 2005 Alpine flood event in Tyrol (Austria), Natural Hazards and Earth System Sciences, 14, 359–378, https://doi.org/10.5194/nhess-14-359-2014, 2014.

Pfurtscheller, C. and Thieken, A. H.: The price of safety: costs for mitigating and coping with Alpine hazards, Natural Hazards and Earth System Sciences, 13, 2619–2637, https://doi.org/10.5194/nhess-13-2619-2013, 2013.

Pfurtscheller, C. and Vetter, M.: Assessing entrepreneurial and regional-economic flood impacts on a globalized production facility, Journal of Flood Risk Management, 8, 329–342, https://doi.org/10.1111/jfr3.12102, 2015.

5 Postance, B., Hillier, J., Dijkstra, T., and Dixon, N.: Extending natural hazard impacts: an assessment of landslide disruptions on a national road transportation network, Environmental Research Letters, 12, 014 010, 2017.

Pregnolato, M., Ford, A., Wilkinson, S. M., and Dawson, R. J.: The impact of flooding on road transport: A depth-disruption function, Transportation Research Part D: Transport and Environment, 55, 67–81, https://doi.org/10.1016/j.trd.2017.06.020, 2017.

Proske, H. and Bauer, C.: Indicative hazard maps for landslides in Styria; Austria, Acta Geobalcanica, 2, 93–101, https://doi.org/10.18509/AGB.2016.10, 2016.

10 Rheinberger, C., Schläpfer, F., and Lobsiger, M.: A Novel Approach to Estimating the Demand Value of Road Safety, FEEM Working Paper, 15, 2017.

Rheinberger, C. M.: A Mixed Logit Approach to Study Preferences for Safety on Alpine Roads, Environmental and Resource Economics, 49, 121–146, https://doi.org/10.1007/s10640-010-9427-9, 2011.

15 Riley, S. J., DeGlaria, S. D., and Elliot, R.: A terrain ruggedness index that quantifies topographic heterogeneity, Intermountain Journal of Sciences, 5, 23–27, 1999.

Ruff, M. and Czurda, K.: Landslide susceptibility analysis with a heuristic approach in the Eastern Alps (Vorarlberg, Austria), Geomorphology, 94, 314–324, https://doi.org/10.1016/j.geomorph.2006.10.032, gIS technology and models for assessing landslide hazard and risk, 2008.

20 Rupi, F., Bernardi, S., Rossi, G., and Danesi, A.: The Evaluation of Road Network Vulnerability in Mountainous Areas: A Case Study, Networks and Spatial Economics, 15, 397–411, https://doi.org/10.1007/s11067-014-9260-8, 2015.

Schlögl, M. and Laaha, G.: Extreme weather exposure identification for road networks – a comparative assessment of statistical methods, Natural Hazards and Earth System Sciences, 17, 515–531, https://doi.org/10.5194/nhess-17-515-2017, 2017.

Schlögl, M. and Matulla, C.: Potential future exposure of European land transport infrastructure to rainfall-induced landslides throughout the 25 21st century, Natural Hazards and Earth System Sciences Discussions, 2017, 1–15, https://doi.org/10.5194/nhess-2017-393, 2017.

Schmaltz, E., Steger, S., Bell, R., Glade, T., van Beek, R., Bogaard, T., Wang, D., Hollaus, M., and Pfeifer, N.: Evaluation of Shallow Landslides in the Northern Walgau (Austria) Using Morphometric Analysis Techniques, Procedia Earth and Planetary Science, 16, 177–184, https://doi.org/10.1016/j.proeps.2016.10.019, the Fourth Italian Workshop on Landslides, 2016.

Schweikert, A., Chinowsky, P., Kwiatkowski, K., and Espinet, X.: The infrastructure planning support system: Analyzing the impact of 30 climate change on road infrastructure and development, Transport Policy, 35, 146–153, https://doi.org/10.1016/j.tranpol.2014.05.019, 2014.

Seijmonsbergen, A. C.: Geomorphological evolution of an alpine area and its application to geotechnical and natural hazard appraisal, dissertation, Vakgroep Fysische Geografie en Bodemkunde, Faculteit Ruimtelijke Wetenschappen, Universiteit van Amsterdam, 1992.

Sørensen, R., Zinko, U., and Seibert, J.: On the calculation of the topographic wetness index: evaluation of different methods based 35 on field observations, Hydrology and Earth System Sciences, 10, 101–112, https://doi.org/10.5194/hess-10-101-2006, https://www.hydrol-earth-syst-sci.net/10/101/2006/, 2006.

Strauch, R. L., Raymond, C. L., Rochefort, R. M., Hamlet, A. F., and Lauver, C.: Adapting transportation to climate change on federal lands in Washington State, U.S.A., Climatic Change, 130, 185–199, https://doi.org/10.1007/s10584-015-1357-7, 2015.

Taylor, M. A. and Susilawati: Remoteness and accessibility in the vulnerability analysis of regional road networks, Transportation Research Part A: Policy and Practice, 46, 761 – 771, https://doi.org/10.1016/j.tra.2012.02.008, network vulnerability in large-scale transport networks, 2012.

Taylor, M. A. P., Sekhar, S. V. C., and D'Este, G. M.: Application of Accessibility Based Methods for Vulnerability Analysis of Strategic Road Networks, Networks and Spatial Economics, 6, 267–291, https://doi.org/10.1007/s11067-006-9284-9, 2006.

Tiroler Tageszeitung: Zufahrt nach Serfaus, Fiss, Ladis mehrere Tage gesperrt, http://www.tt.com/panorama/natur/14119342-91/zufahrt-nach-serfaus-fiss-ladis-mehrere-tage-gesperrt.csp, accessed: 2018-03-13, 2018.

Unterrader, S., Almond, P., and Fuchs, S.: Rockfall in the Port Hills of Christchurch: Seismic and non-seismic fatality risk on roads, New Zealand Geographer, pp. n/a–n/a, https://doi.org/10.1111/nzg.12170, 2017.

van Asselen, S. and Seijmonsbergen, A.: Expert-driven semi-automated geomorphological mapping for a mountainous area using a laser DTM, Geomorphology, 78, 309–320, https://doi.org/10.1016/j.geomorph.2006.01.037, 2006.

van Westen, C. J., Castellanos, E., and Kuriakose, S. L.: Spatial data for landslide susceptibility, hazard, and vulnerability assessment: An overview, Engineering Geology, 102, 112–131, https://doi.org/10.1016/j.enggeo.2008.03.010, landslide Susceptibility, Hazard and Risk Zoning for Land Use Planning, 2008.

Varnes, D.: Landslide hazard zonation: a review of principles and practice, Engineering Geology, 102, 112–131, united Nations Educational, Scientific and Cultural Organization, 1984.

Vera Valero, C., Wever, N., Bühler, Y., Stoffel, L., Margreth, S., and Bartelt, P.: Modelling wet snow avalanche runout to assess road safety at a high-altitude mine in the central Andes, Natural Hazards and Earth System Sciences, 16, 2303–2323, https://doi.org/10.5194/nhess-16-2303-2016, 2016.

VoGIS: Land Vorarlberg: Online-Zählstellenkarte, http://vogis.cnv.at/atlas/init.aspx?karte=strassenzaehlstellen&ks=verkehr, accessed: 2018-03-13, 2018.

Winter, M. G., Shearer, B., Palmer, D., Peeling, D., Harmer, C., and Sharpe, J.: The Economic Impact of Landslides and Floods on the Road Network, Procedia Engineering, 143, 1425–1434, https://doi.org/10.1016/j.proeng.2016.06.168, advances in Transportation Geotechnics III, 2016.

Yin, H.-y. and Xu, L.-q.: Measuring the structural vulnerability of road network: A network efficiency perspective, Journal of Shanghai Jiaotong University (Science), 15, 736–742, https://doi.org/10.1007/s12204-010-1078-z, 2010.

Yin, J., Yu, D., Yin, Z., Liu, M., and He, Q.: Evaluating the impact and risk of pluvial flash flood on intra-urban road network: A case study in the city center of Shanghai, China, Journal of Hydrology, 537, 138–145, https://doi.org/10.1016/j.jhydrol.2016.03.037, 2016.

Yokoyama, R., Shlrasawa, M., and Pike, R. J.: Visualizing Topography by Openness: A New Application of Image Processing to Digital Elevation Models, Photogrammetric Engineering and Remote Sensing, 68, 257–265, 2002.

Zêzere, J., Pereira, S., Melo, R., Oliveira, S., and Garcia, R.: Mapping landslide susceptibility using data-driven methods, Science of The Total Environment, 589, 250–267, https://doi.org/10.1016/j.scitotenv.2017.02.188, 2017.

Zieher, T., Perzl, F., Rössel, M., Rutzinger, M., Meißl, G., Markart, G., and Geitner, C.: A multi-annual landslide inventory for the assessment of shallow landslide susceptibility – Two test cases in Vorarlberg, Austria, Geomorphology, 259, 40–54, https://doi.org/10.1016/j.geomorph.2016.02.008, 2016.

Zischg, A., Fuchs, S., Keiler, M., and Stötter, J.: Temporal variability of damage potential on roads as a conceptual contribution towards a short-term avalanche risk simulation, Natural Hazards and Earth System Sciences, 5, 235–242, https://doi.org/10.5194/nhess-5-235-2005, 2005.