Quantitative landslide risk assessment in the city of Tuzla

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Abstract

In the climate-changing conditions, geological environment interacts more dramatically with the urban fabric than before. The urbanization is expansive and more aggressive than before, but so are the weather extremes and long-term climate trends. In effect, many processes which can be triggered by either side, nature or engineering, are becoming more pervasive than before, and such is the case with landslides. Dealing and managing landslides requires few crucial steps, starting from collecting data on landslide location and typology – inventorying, estimating zones of their spatial probability exceedance, appending zones of their increased temporal probability for a given return period, and finally, estimating which elements at risk these exceeded probabilities can affect and at what level. In this work, a practical case is represented to illustrate all these steps and demonstrate successful implementation of complete landslide assessment (from landslide inventory to risk or early-warning system). The practical example considers the case of the City of Tuzla in Bosnia and Herzegovina, which is known for instabilities due to rugged steep slopes, but also destabilizing effects of underground and open pit mining, which has a long tradition in Tuzla. However, the main motive for considering this case study lies in severe landslidng episode triggered during the heavy rainstorm in mid-May 2014. The landslide inventory was compiled by a combination of historic and post-2014 field reports, while all other inputs, including geological, geomorphologic and environmental factors were coming from a separate detailed study on flooding and landsliding hazard in the City of Tuzla. The inventory of element at risk, in this case the housing sector, represented by weighted population density, was also very important input, which needed to be prepared cautiously, using as realistic estimations on population distribution as possible. Eventually, overlapping spatial and temporal dimension of the process, as well as detailed element at risk inventory, resulted in a very detailed, very realistic landslide risk map. The map depicts realistic risk distribution over the populated areas. Intermediate models, such as susceptibility, exposure, hazard etc., as well as the final risk model suggests good performance, both visually and numerically (high accurancy >75% and AUC of >0.85) and justifies landslide assessment in the future for many aspects of urban planning and related decision-making.

1 INTRODUCTION

Urban sprawl tends to consume larger and larger portions of natural environment. In response, the interaction between urban and natural can be violent from both sides. For instance, the fragile balance of the natural slopes is undermined by slope cuts and de-vegetation for infrastructure and construction, which is compensated by intensifying erosional and landslide processes, subsidence etc. On top of that, unstable or extreme weather in the climate changing conditions can further cause that such engineering activities might be overcompensated, and that natural response might result with disasters (Haque et al. 2016). Planners and decision-makers should become aware of such scenarios and anticipate for specific risks when planning infrastructural and other urban development. It is even more pronounced in the developing countries, which are entirely focused on infrastructural development, and cannot additionally cope with the disasters. They usually reach their financial limits just by entering constructional investment, leaving any possible disaster effects uncovered, perhaps even unaccounted for (Mutter, 2015). For this reason, large scale disaster assessment needs to be practiced and more involved in the legislation. It allows a better insight into critical parts, allows prioritization, and hence, better planning and preparedness in the case of emergency.

This paper precisely addresses such issues in a case study of the City of Tuzla in Bosnia and Herzegovina (BiH). The city is well-known for its mining activities, which bring welfare into the region and stimulate urban development. On the other hand, it is also known for rugged, steep terrain, hostile geological environment, underground mining side-effects (settlement), which is why it has been chosen for a focused study of the UNDP BiH office in 2015-16. The principal objective of the study was to delineate dwelling zones under high landslide and flood risk. Herein, only the part on landslide risk will be considered and presented.

2 METHODOLOGY

Landslide susceptibility, hazard and risk assessment (LSA) procedures are nowadays well defined, but still very versatile depending on the purpose, scale and level of detail (Fell et al. 2008). It is a very proliferating field of research with numerous year-to-year innovations, regarding the techniques for semi-automated landslide inventorying, new algorithms for improved landslide susceptibility assessment, advances in involving hazard component into the analysis, complete solutions from inventory to risk, as well as early-warning systems development as a final stage and purpose of LSA (Dai et al., 2002). We have addressed several of these state-of-the-art aspects in our recent work, as well (Marjanović 2014; Marjanović et al. 2019; Đurić et al. 2019). However, it is evident that hazard and risk, as final stages of the assessment are subordinate to the quantity of studies and practices of landslide inventorying and susceptibility (Gokceoglu & Sezer, 2009; Sudhakar et al. 2013). Herein, it is attempted to complete the full scope from landslide inventorying to societal landslide risk quantification.

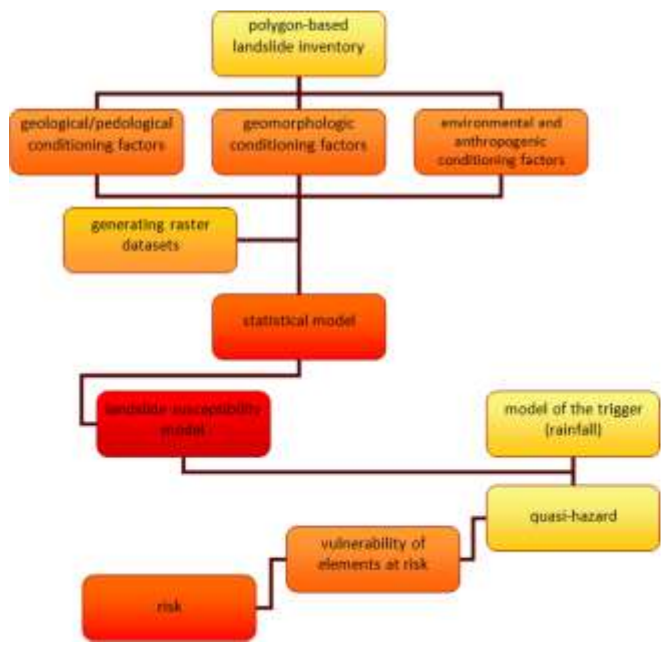

Figure 1. Flow chart of the modeling procedure.

The following sequence of techniques and procedures (Fig. 1) was implemented to that end

- Landslide inventorying: compiling long-term landslide event records throughout the city territory, from geotechnical reports, field campaigns (especially from 2014), remote sensing image analysis; using point or polygon for landslide representation, based on landslide size; filtering only appropriate, shallow landslides, of sufficient size for the final inventory.

- Landslide susceptibility: collecting causative-conditioning factors as proxies for landsliding process propagation, including geological, geomorphologic and environmental factors, as well as synthetic GIS-based derivatives; splitting the area into training and testing/validating parts; training the Machine Learning algorithm, Support Vector Machines in particular, over a reasonable training sample size (25-33%) using landslide inventory as a reference; establishing connection between landslide and non-landslide occurrences against the conditioning factors – optimizing the model – fitting the classification function; applying the classification function to the unseen instances in the remaining testing/validating area; outputting a map of extrapolated landslide and non-landslide pixels over the entire area of interest.
- Landslide quasi-hazard (Marjanović & Đurić, 2016; Marjanović et al., 2019): interpolating annual rainfall distribution for specified period (baseline, or specific future projections) from the point-based data (weather stations); normalizing obtained rainfall map to 0-1 range; overlapping previously completed susceptibility model and normalized rainfall map for obtaining quasi-hazard, thereby delineating areas that are prone to landslides both spatially and temporally (temporal dimension through the designated rainfall period, i.e. annual).
- Element at risk inventorying: housing sector as element at risk, mapped on the basis of building structure and average population density per unit; building structure polygon database; average population density allocated per dwelling unit; population density normalized to 0-1 range.
- Distance-based vulnerability assessment: producing map of distance from the zone of high (H) susceptibility outward; inversing the value so that adjacent areas are penalized with highest scores, while remote areas receive smallest distance values (the closer pixel is to the H zone higher the exposure); normalizing distance-based exposure to 0-1 range; allocating value 1 inside the H class.
- Risk assessment: overlapping Vulnerability and Element at risk maps; normalizing to 0-1 range.

3 STUDY AREA

The City of Tuzla in BiH spreads over approximately 294 km^2 of mostly rugged and steep hilly terrain (Fig. 2). The city is known for its underground and open pit mining tradition, but also suffers from related ground instabilities (especially subsidence), but the actual motivation for a detailed study was the 2014 massive flooding and landslidng event that affected the entire region (Fig. 3). More than 500 mm was precipitated in less than a month and a half, which is more than 6 months' worth of rainfall in normal conditions. A detailed landslide risk assessment study, using SVM Machine Learning technique (Marjanović et al. 2011) for susceptibility assessment and high-resolution data for landslide and elements at risk inventories was undertaken using all steps indicated in the previous chapter.

Figure 2. Location of the City of Tuzla in the South Europe.

Figure 3. Cumulative precipitation in April-May 2014 in Tuzla.

The landslide inventory was compiled using historic (pre-2014) and field data gathered after 2014 for 113 km^2 urban territory of the City of

Tuzla. It was produced as a high-resolution polygon-based inventory, but it lacked desirable metadata, such as landslide typology, mechanism, metrics etc. Still, some filtering on the basis of the landslide shape and size was performed to limit the inventory classes to similar, shallow sliding or flowing events. Simple non-landslide, landslide and marginally stable slope classes were eventually defined in the inventory. It was subsequently converted from polygon-based to a 5 m resolution raster. All other raster data had the same 5 m resolution.

Landslide susceptibility required several static conditioning factors used as proxies for the landsliding process. These included geological, geomorphologic and environmental data. These were subsequently supplemented with dynamic input, represented by the specific rainfall map, to allow for a quasi-hazard modeling.

3.1 Geological factors

Geological factors were extracted from the engineering geological map at 1:10000 scale and included the following separate geological proxies: engineering geological units, hydrogeological units and distance to hydrogeological boundaries. Engineering geological units were classified on the basis of engineering properties. All rocks with similar cohesion and compactness were aggregated together. Proposed SVM technique requires separation of nominal classes, given in the original and aggregated map, into sets of binary variables, so that each class gives a new sub-variable. For instance, engineering geological units were segregated into 9 sub-variables (9 new rasters), that are binary (1 = observed engineering geological class, 0 = union of all other engineering geological classes).

Hydrogeological units were classified on the basis of their hydrogeological function, thereby additionally highlighting differences between engineering geological units in contact zones, which are considered prone to landslides. Distance to hydrogeological boundary between units of different hydrogeological function is hence included as a separate proxy. It is generated by calculating Euclidean distance of each pixel from the extracted hydrogeological boundary.

3.2 Geomorphologic factors

Geomorphologic factors included a set of commonly used morphometric parameters (van Westen, 2003): elevation, slope, aspect and curvature. These were all obtained directly from 5 m resolution Digital Terrain Model (Fig. 4). Geomorphologic proxies also included distance to hydrographic network, i.e. streams and rivers which were also extracted from DTM as vector lines. Subsequently, Euclidean distance from this line vector was calculated for each pixel in the area of interest. All these represent numeric variables, which were further normalized to 0-1 range.

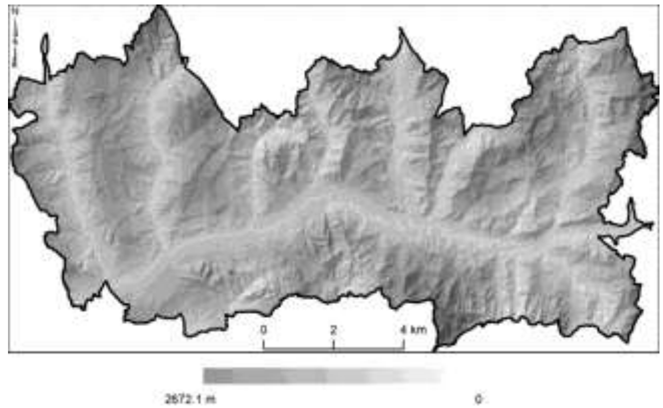

Figure 4. Digital Terrain Model of the study area.

3.3 Environmental factors

Environmental proxies included land cover classes developed through comprehensive mapping of elements at risk. This raster dataset was nominal, just as in the case of engineering geological units, so the same procedure of its aggregation into dummy variables was followed. Distance to mining sites was calculated to depict disturbed zones, since mining in Tuzla region includes open pit coal and underground salt mining. Both mining types can affect stability by causing subsidence (m order of magnitude) or producing waste deposits that are fine-grained non-cohesive but unstable when saturated. Distance to mining is a numeric proxy, which was normalized to meet 0-1 span of values.

4 RESULTS

The landslide susceptibility map (Fig. 5) visually showed a good match with the referent landslide inventory. The accuracy estimators also support this view. The accuracy went over 75%, while AUC of landslide classes was above 0.85 as well as marginally stable slope class, which indicates that the biggest source of error remained within the stable slope class (AUC=0.75).

Landslide susceptibility led to quasi-hazard mapping that was generated by multiplying landslide susceptibility with according historical rainfall scenario of average annual rainfall for

1981-2010 baseline period (Fig. 6), obtained by interpolation of the available weather station point data. Further maps might involve any other available historic period as a baseline, or even future projections, to enclose potential climate change effects.

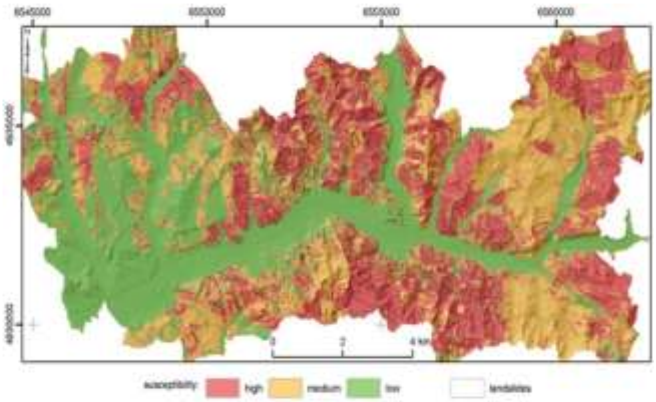

Figure 5. Landslide susceptibility model of the area.

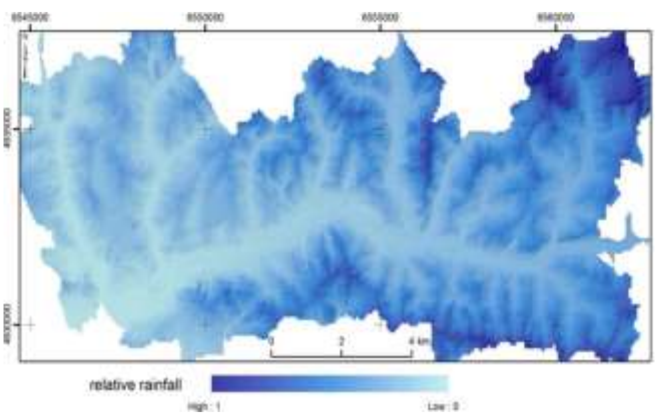

Figure 6. Annual rainfall distribution map of the area.

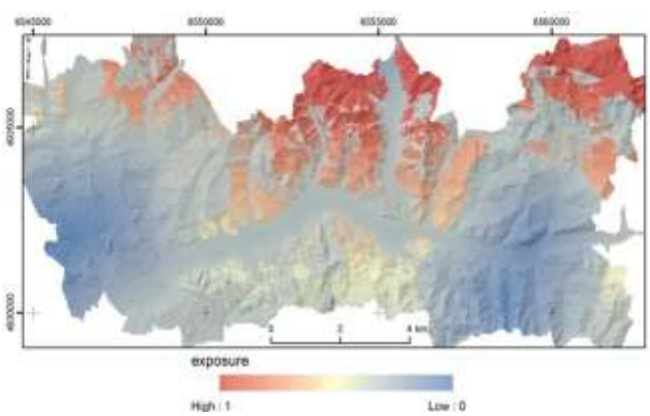

Figure 7. Exposure vulnerability map of the area.

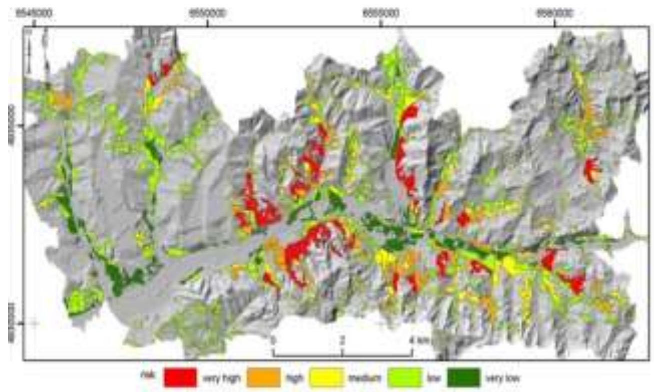

Figure 8. Landslide risk map of the area.

After obtaining the susceptibility classes distribution it was further possible to calculate weighted distance to the H landslide susceptibility class. Resulting exposure vulnerability map (Fig. 7) was superimposed to the inventory of elements at risk, to obtain the final relative risk (Fig. 8). Only the housing sector land use types entered the inventory of elements at risk, since only these had precise population estimates per block. The final map was averaged across housing blocks, since they represent the target risk units.

5 DISCUSSION AND CONCLUSION

Figures 5-7 indicate an excellent example on how including additional tools to the common landslide susceptibility assessment refines the analysis. Typical classification task performed by using SVM in this particular case, normally outputs specific landslide classes. In this case class replication was as follows: non-landslides were map into low susceptibility, marginally stable slopes into medium susceptibility, whereas landslides were mapped into high susceptibility class. Most of the high and medium class was identified along steep valley slopes and higher terrain, but seemingly the class seems overestimated. Further refinement was performed by introducing normalized rainfall trigger, as a temporal (annual) factor of landslide reoccurrence. If landslides are likely to be triggered by rainfall, then the most hazardous will be the areas with most frequent and most intensive rainfall (depicted in dark blue), i.e. higher terrain. Combination of these two maps (Fig. 5-6) introduces continuous not discriminant landslide class, ranging from 0-1. Similarly, exposure vulnerability, expressed by the inverse distance, refines the range by highlighting the areas close to high susceptibility class even further. Comparing Figure 5. and Figure 7. shows that the maps can be significantly refined by introducing additional spatial and temporal factors. In Figure 5. all areas falling in the high class were equal, while important details within this class is introduced in Figure 7., which reveals the differences within the high susceptibility class. Finally, the housing sector population density introduces final refinement and an actual relative risk assessment, as it further highlights the populated areas. For instances, areas which are not populated or scarcely populated do not exhibit high risk despite the fact they fall within high susceptibility or high hazard class. On the other hand, model needs to remain realistic also in the case of high population density but low susceptibility or hazard. Both two cases should remain within the low risk, whereas high risk should be reserved for populated areas with considerable hazard to landsliding.

Validation was achieved through comparison of the high landslide susceptibility class against landslide inventory instances. God match of over 75% of accuracy and AUC of 0.85 was achieved in landslide susceptibility model. The same can be expected for all subsequent models which incorporate the susceptibility model, such as hazard and exposure. On the other hand, risk model cannot be easily validated. Visually it corresponds well with both, the inventory of landslides and inventory of elements at risk (Fig. 9). Very high risk covers significant area, i.e. over 4 km^2 or 16%. Visually, it is evident that model well recognizes highly populated areas along the main valley and mainly leaves them in low risk as they are flat and landslide free areas. On the other hand, a good overlap of populated areas and landslide prone areas is achieved (overlap of red and purple polygons in Fig. 9).

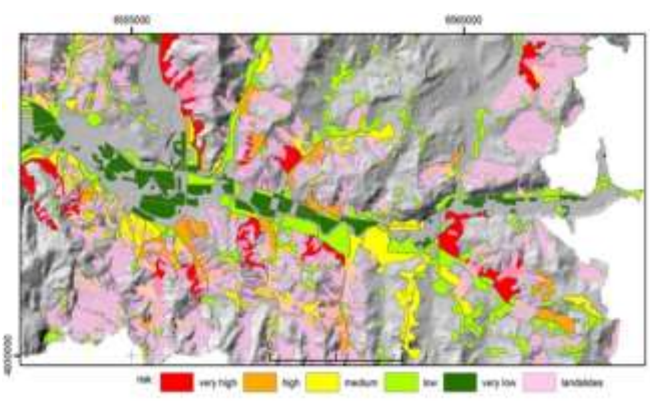

Figure 9. Detail of the Landslide risk map overlapped with the landslide inventory.

Presented practical example of the City of Tuzla shows how the landslide assessment can be put in practice, starting from the inventory compilation, all the way to risk assessment. Risk over the population is a quantitative value well-understood by the responsible decision-makers and planners, while landslide susceptibility, exposure, vulnerability and hazard are less understandable concepts in their common practice. This is another reason why complete assessment, all the way to the risk, becomes essential, and why such research should be stimulated in the future, as there is an evident lack of such. Only successful communication between all parties is the guarantee of better urban planning, good investment, proper remediation and prevention, fast emergency response, and other aspects of landslide risk management.

6 ACKNOWLDEGEMENTS

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