Land subsidence susceptibility mapping for Hanoi city, Vietnam

R. Arnhardt[1], A. Novellino[1], E. Hussain[1], L. Bateson[1], A. Newell[1]

1 British Geological Survey, Nottingham, United Kingdom

raus@bgs.ac.uk

Introduction

Land subsidence is one of the main issues in Vietnam, especially in Hanoi, due to the urban growth and its associated excessive consumption of natural resources such as groundwater and increased construction. This abstract describes the assessment of land subsidence in Central Hanoi by using InSAR, engineering geological characteristics obtained from boreholes and a weight of evidence statistical method. The result is presented as a land subsidence susceptibility map.

Study area

Hanoi is the capital city of Vietnam located within the Red River Delta. Geologically the city consists of unconsolidated Quaternary sediments of fluvial and marine origin (50-90m deep), resting on Neogene deposits (Trafford, 1996). Regarding engineering geology, Quaternary sediments are divided into 24 layers starting from man-made soils on the upper part (sandy clay with mixture of construction materials) to Le Chi formation at the bottom, which consists of grey and brown clayey sand with gravel (Phi & Strokova, 2015). Regarding hydrogeology, Holocene and Pleistocene aquifers are the key aquifers of the city which are mainly recharged from the Red River in an approximately 5 km wide zone (Berg et al., 2008).

Urban growth in Hanoi and land subsidence

Hanoi city is the second largest city of the country with 7.4 million inhabitants, however, the population is projected to reach 9–9.2 million by 2030 and approximately 10.8 million by 2050 (Kubota et al., 2017). Such growth in urban habitants in Hanoi is placing significant pressure on existing land and resources and resulted in substantial land cover changes (Novellino et al., 2021). Additionally, it has also caused increased consumption of natural resources, such as groundwater. The rate of groundwater abstraction has been increasing rapidly and since the 2000s, the number of private wells used for factories and households has been growing. This unregulated groundwater usage presents a risk of declining groundwater levels and associated ground subsidence, which is one of the main hazards in the city.

Data and methodology

To investigate the land subsidence, the test area (22 x 25km) is restricted to central Hanoi due to the limited borehole data availability. For contributing factors to subsidence, from the 271 boreholes, lithology proportions (clay, fine-medium sand and medium-coarse sand) are extracted. The borehole records are exported to GOCAD software to build a 3D model of the area. Figure 1 displays the geographical distribution of boreholes and a selected area on the left-hand side of the image and the constructed 3D geological model on the right.

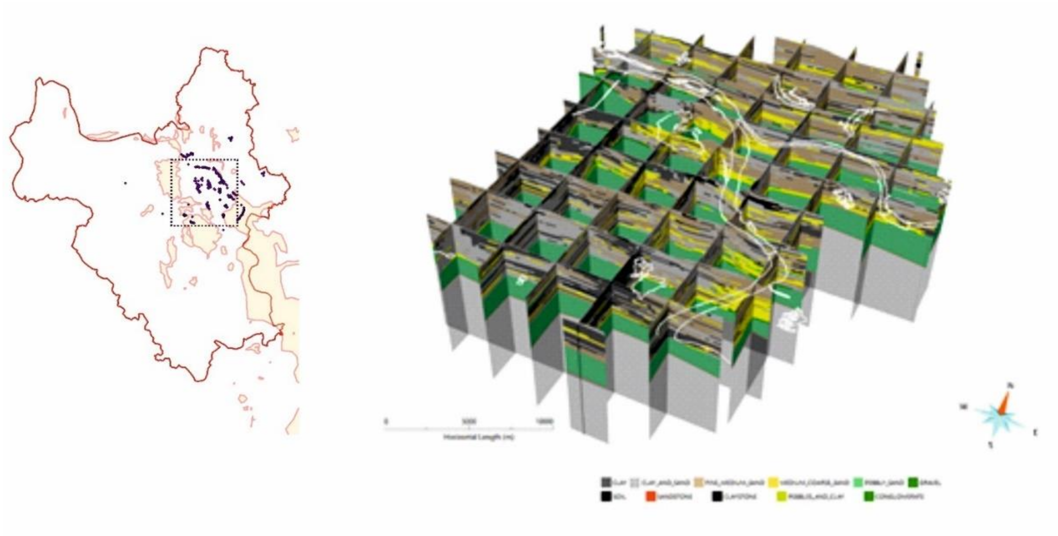

Figure 1 Geographical location of boreholes and 3D geological model of the Central Hanoi area

From the 3D geological model, the proportions of clay, fine-medium sand, and medium-coarse sand are extracted in a raster format with a cell size of 1 x 1 km. The thicker proportion of clay is observed in the west and south parts of the area, whereas fine-medium sand is distributed mainly in the north and south-east of the area. Medium-coarse sand can be seen in the south-east and in the central parts (Figure 2).

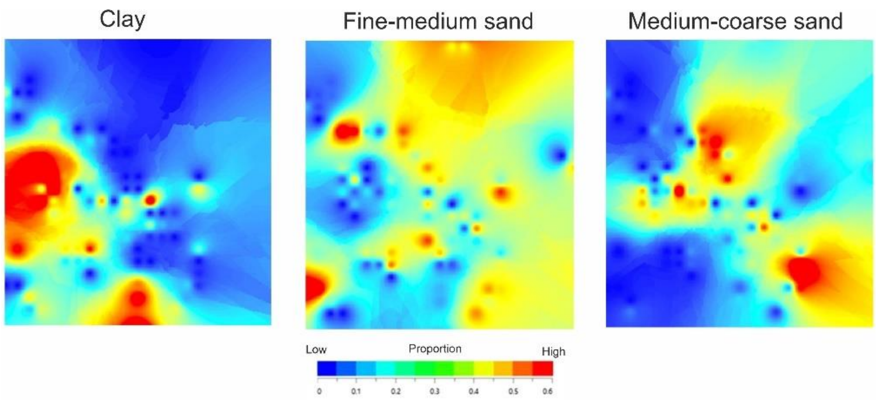

Figure 2 Proportion of clay, fine-medium sand and medium-coarse sand. The legend shows from blue to red which means the proportion is gradually increasing.

To model susceptibility, a subsidence inventory map is required, however due to unavailability of such data, InSAR images are used to extract subsiding areas. For the InSAR analysis we downloaded 147 Single Look Complex (SLC) Sentinel-1 images from descending track 91, spanning 2 July 2015 to 7 January 2021 and used these images to form 291 interferograms using the Interferometric synthetic aperture radar Scientific Computing Environment (ISCE) software (Rosen et al., 2012). To improve the signal-to-noise ratio we multilooked each image by 9 pixels in range and 3 pixels in azimuth giving pixel sizes of approximately 50 m. For the InSAR time series analysis we processed the 291 small baseline interferogram stack using the Miami InSAR Time-series software in PYthon (MintPy) (Yunjun et al., 2019). This resulted in a geocoded line-of sight displacement time series for every pixel in the dataset. The average velocity through the time series is shown in Figure 3.

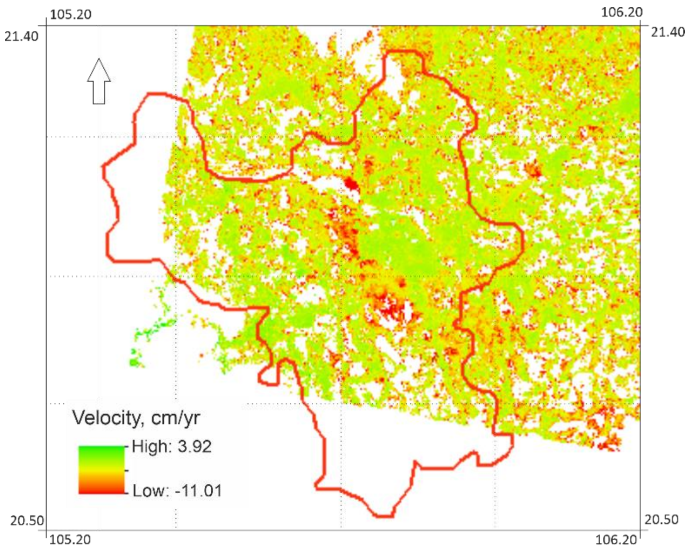

Figure 3 The average line-of-sight velocity from the InSAR time series analysis. Red colours represent range increase from the satellite.

We ran a Principal Component (PC) analysis on the InSAR time series and considered the first seven PCs to guide the clustering of the InSAR time series. Clustering is an unsupervised machine learning technique where an algorithm groups similar data points starting from a collection of unlabelled data (Hubert & Arabie, 1985). In this work the Euclidean K-means algorithm has been used to cluster the standardised InSAR time series. The K-means algorithm clusters data by trying to separate samples in n groups of equal variances, minimizing a criterion known as the inertia or within-cluster sum-of-squares and this algorithm requires the number of clusters to be specified. The code used for the post-processing of the InSAR results is available on GitHub at https://github.com/Alessandro13751/InSAR_clustering. The results are shown in Figure 4.

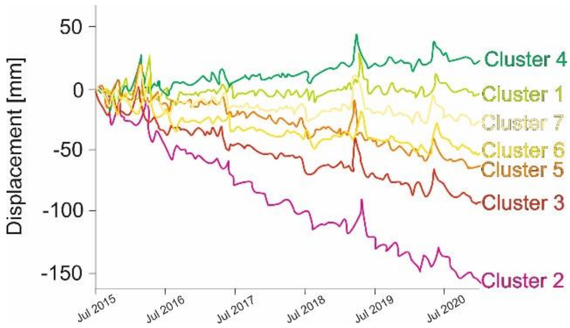

Figure 4 K-means clustering for seven groups

Of the 4,377,112 points analysed, the majority belong to cluster 1 (30.5%), 4 (26.9%) and 6 (20.3%). The clusters associated to the fastest subsidence rates (2 and 3) account for ~7% of the total population. Following the clustering method, it is possible to highlight areas with the fastest rates of subsidence, specifically 2, 3, 5, 6 that were used for the analysis. The points belonging to these clusters were extracted by using ArcGIS tool "selection".

After this step, the point data were transformed to raster data with resolution of 1 x 1km. For this work a bivariate statistical method such as weight of evidence based on Bayes theorem was used (Bonham – Carter et al.,1989). Land subsidence susceptibility index was created by overlaying rasters of contributing factors in GIS. To use a supervised classification approach, the raster data from InSAR are randomly divided into two groups where one group (80%) is assigned to train the model, the other to test it (20%). By overlaying maps of contributing factors (proportion of clay, fine-medium sand and medium-coarse sand), land subsidence susceptibility is developed. Validation is carried out by using Receiver Operating Characteristic curve (ROC), a graph showing how the classification model was performed which plots true positive rate and false positive rates. In addition, an area under curve (AUC) value is used to assess the performance of the model.

Results and discussion

The susceptibility map presented in Figure 5 depicts the high susceptible areas to subsidence are located in the south-west and in the north-west. High clay proportion also identified in these areas (Figure 2). The result of the AUC-ROC curve for the model is 0.7. The AUC value ranges from 0 to 1 implying the higher the value the better the performance. If the value is from 0.9 – 1 the model performance can be classified as excellent, 0.8 – 0.9 very good, 0.7-0.8 – good, 0.6 – 0.7 average and under 0.6 is poor performances (Yesilnacar & Topal, 2005). Therefore, the result can be classified as average to good model accuracy.

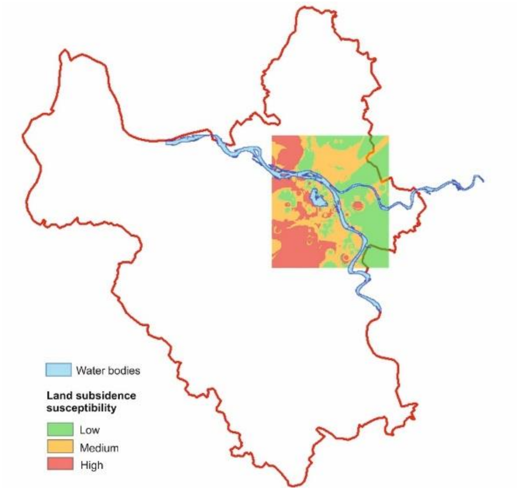

Figure 5 The results of the susceptibility mapping for Central Hanoi

These results could be improved by using better resolution data. In addition, borehole records for a larger area will allow obtaining a proportion of lithologies for a more expansive space; therefore, it would be beneficial to extend the study area. In situ land subsidence monitoring data would also allow improving the results. Even though the model accuracy is not in an excellent range, from this study, it is possible to draw initial evaluation of high subsidence areas in Central Hanoi. This susceptibility map could be used for strategic planning by decision makers, urban planners, and engineers to identify subsidence risk.

Conclusion

This work aims to evaluate land subsidence issues in Hanoi by using InSAR techniques and develop a susceptibility index for the study area. Due to data scarcity, only geological factors such as the proportion of lithologies are used as the contributing factors. The results of the InSAR dataset are used as a land subsidence inventory map. The resolution of the data was 1 x 1 km for a study area of 22 x 25 km. The susceptibility model obtained by using a weight of evidence method shows that the accuracy of the model prediction is average. However, it could be improved by using additional data.

References

Berg, M., Trang, P T K., Stengel, C, Buschmann J., Viet P H., Nguyen V D., Giger W., Stueben D. 2008. Hydrological and sedimentary controls to arsenic contamination of groundwater in the Hanoi area, Vietnam: The impact of iron – arsenic ratios, peat, river bank deposits, and excessive groundwater abstraction. *Chemical Geology*, Issues 1-2, 91-112

Bonham-Carter, F., Agterberg, F.P., Wright, D F. 1989. Weights of evidence modeling: a new approach 360 to mapping mineral potential. *Statistical applications in the earth sciences*, 171–¬183

Hubert, L., Arabie, P., 1985. Comparing partitions. *Journal of classification*, 2(1), pp.193-218

Kubota, T., Lee, H.S., Trihamdani, A.R., Phuong, T.T.T., Tanaka, T. and Matsuo, K., 2017. Impacts of land use changes from the Hanoi Master Plan 2030 on urban heat islands: Part 1. Cooling effects of proposed green strategies. *Sustainable cities and society*, 32, pp.295-317.

Novellino, A., Brown, T.J., Bide, T., Thuc Anh, N.T., Petavratzi, E., Kresse, C., 2021. Using Satellite Data to Analyse Raw Material Consumption in Hanoi, Vietnam. *Remote Sensing*, 13(3), p.334

PHI, T H., Strokova, L A., 2015. Prediction maps of land subsidence caused by groundwater exploitation in Hanoi, Vietnam. *Resource – Efficient Technologies*, Vol. 1, Issue 2, 80–¬89

Rosen, P.A.; Gurrola, E.; Sacco, G.F.; Zebker, H. 2012. The InSAR Scientific Computing environment. *In Proceedings of the 9th European Conference on Synthetic Aperture Radar, EUSAR 2012, Nuremberg, Germany,* 23–26 April 2012; pp. 730–733

Trafford, J M., Lawrence, A R., MacDonald, D M J., Nguyen, V D., Dang, N T., Nguyen, T H. 1996. The effect of urbanization on the groundwater quality beneath the city of Hanoi, Vietnam. *British Geological Survey Technical Report, WC/96/22. Overseas Geology Series, Name of Academic or Technical Journal*, Vol. 12, 345–¬378

Yesilnacar, E N, Topal, T 2005. Landslide susceptibility mapping: A comparison of logistic regression and neural networks method in a medium scale study, Hendek region (Turkey). *Engineering Geology*, Vol. 79, 251–¬265

Yunjun, Z.; Fattahi, H.; Amelung, F. Small baseline InSAR time series analysis: Unwrapping error correction and noise reduction. *Comput. Geosci*. 2019, 133, 104331