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A NEW GIS-BASED TECHNIQUE USING FUZZY FOR LAND SUBSIDENCE SUSCEPTIBILITY MAPPING

M.VISHNU TEJA, D.CHANDRASEKAR, N.SRI CHANDRAHAS

Department of Mining Engineering, Malla Reddy Engineering College (Autonomous)

ABSTRACT

Ground subsidence susceptibility at a coal mine by integration of L-band SAR measurements and a subsidence hazard model incorporated in GIS was estimated. A subsidence hazard map was constructed using JERS-1 SAR data from the early 1990s and the subsidence hazard model. A certainty factor analysis was employed for estimating the relative weights of four control factors influencing coal mine subsidence. The relative weight of each factor was then integrated to generate a subsidence hazard index (SHI) by a fuzzy combination operator. The hazard map was validated by comparison with subsidence observed by ALOS PALSAR interferometry in 2007-2008. The results showed a good agreement between the predicted locations vulnerable to subsidence and the actual subsidence occurrences with an accuracy of about 72.5%. These results showed that the map produced by integration of InSAR and GIS can be used to predict and monitor coal mine subsidence hazards, especially in remote regions.

INTRODUCTION

Ground subsidence over the Nobi Plain is a natural phenomenon occurring due to natural compaction of the soft sedimentary layers of the plain and the tilting of the Nobi geomorphologic structure itself. Subsidence rate of 23 cm/year was recorded at an observational point in Minato Ward, Nagoya, in 1973. However, such a large-scale subsidence cannot be explained by the above-mentioned factors alone. The acceleration of compaction and contraction due to falling groundwater levels can be pointed as one of the other major man-made factors with potentially remarkable impacts. These falling levels are a consequence of the fast increase in pumping ground water following the rapid postwar economic growth over the area, and which could not be matched by natural replenishment of ground waters. Similar ground level subsidences have also been reported in relationship with the overexploitation of ground waters in many other parts of the World (see for a detailed review).

This ground subsidence over the Nobi Plain became well known following the Ise-wan Typhoon (Typhoon Vera) in autumn

1959. In its Annual Report in 2000, the Land Subsidence Survey Committee of the Three Prefectures in Tokai Region reported that, after the 1959 typhoon, a gradual expansion of the subsidence area peaking in 1973–1974 was observed, followed by a slowing trend in subsidence activity since then, more likely because of such factors as the strengthening of regulations concerning groundwater pumping. We have to note here that very few researches have been performed on this subject so far, notwithstanding the remarkable ground subsidence still observed to occur in some areas of this Plain, even nowadays, or the rising grounds found in many other parts. These changes in ground level conditions are likely to imperil the foundations of life-sustaining infrastructures in this area, including damages to build up structures, especially in the case of tsunamis or sea level increase due to the global warming. All these facts are a great source of concern for residents in the region.

The analysis on ground changes by InSAR can be expected as in recent years, interferometric synthetic aperture radar (InSAR) technology has been more and more in use to estimate with high precision the spatial distribution of changes in the Earth's crust surface height and the amount of such changes at each specific location. This new approach can be considered as a complementary method to by traditional standard measurements for monitoring ground subsidence. More specifically, ground level subsidence reported in relationship with the overexploitation of ground waters has been analyzed using InSAR techniques in many parts of the World. This is the case of Lisbon in Portugal, the Pingtung Plain and the Chousui River Alluvial Fan in Taiwan, the Campania Region and Bologna in Italy, as well as Kolkata City in India. It is expected the InSAR techniques, as well as its more recent variants such as the PSInSAR, will become powerful complementary, or even substitute, methods to traditional ground subsidence observation using leveling and other methodologies used so far.

Changes in atmospheric water vapor are extremely complex, with 3-dimensional changes taking place not only in the vertical, but also in the horizontal directions. It is extremely difficult to correct for the local effects of water vapor when local aerological data are not available. The PSInSAR method attempts to handle this issues by temporal averaging of up to 30 SAR images. Conventional researches with respect to the atmospheric impacts on InSAR mainly examine the effects of changes in atmospheric water vapor with altitude, limiting therefore the precision of this methodology in most of the past studies on atmospheric delay using InSAR techniques.

In this study, using GIS as analytical platform, we aim at estimating the spatial variation and the temporal changes in ground subsidence over the Nobi Plain using both ground level measurements data and InSAR data. However, notwithstanding the availability of weather charts and detailed information of ground surface atmospheric conditions (temperature, pressure, water vapor, wind, etc.) over Japan during the JERS-1 period (1992–1998), detailed information for upper atmospheric layers has been made available by the Japan Meteorological Agency only after 2002 with its multi-layer and multi-temporal Grid Point Value of Meso-Scale Model (GPV-MSM) data set (see Section 2.2 for details). We therefore propose to use the Analog Weather Chart (hereafter, AWC) method [35,36] in order to estimate from the analog GPV-MSM weather charts and datasets those water vapor inputs needed for calculating water vapor effects on the JERS-1 SAR interferometry data.

Data generation for training and testing

In this subsection, we summarize the generation process of our training and test data. There are some common surface deformation measurement systems that are used to monitor and measure land subsidence, such as precise theodolite vertical angles and electronic levels (Savvaidis 2003). These common systems are really useful, and the approximated accuracies are close to 10 mm. They are straightforward and suitable for small regions (Koros and Agustin 2017). Furthermore, since these systems are ground point-based, they are usually affected by some problems in the process of field surveying and information gathering (Nagaomo et al. 2007). Nowadays, monitoring of ground deformation hazards such as land subsidence is possible using remote sensing satellites. The land subsidence inventory database of the study area was created using DInSAR data. In this study, the interferometric wide swath (IW) modes of Sentinel-1 images were used for further processing. This satellite (launched by the European environmental monitoring program Copernicus in 2014) presents synthetic aperture radar (SAR) data for ground deformation applications (Yu et al. 2017). Two sets of SAR images acquired at different times are the main input for the approach (Barra et al. 2017). To avoid the impacts of vegetation cover changes our first and second selected images were taken on 22 August 2015 and 22 August 2017, respectively. The Sentinel-1 IW interferometric pair was coregistered by the precise orbit state vectors and DEM (Jiang et al. 2017).

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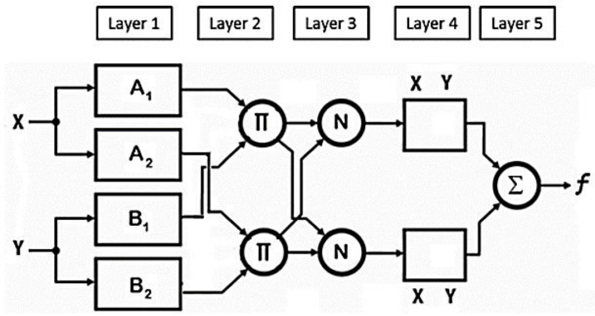
The next step was to generate an interferogram. Because Sentinel-1 applies the TOPS (Terrain Observation by Progressive Scan) imaging mode (De Zan and Guarnieri 2006), it is able to cover a wide area (Yagüe-Martínez et al. 2016). This leads to images being captured within a series of overlapping regions (Czikhardt et al. 2017). Therefore, the small difference within overlap bursts is advantageous for retrieving the horizontal motion of the ground parallel to the satellite path (Grandin et al. 2016). The noise of these bursts was removed in a de-bursting process. De-bursted stacks were used to subtract the topographic phase. A Goldstein filter (Goldstein and Werner 1998) was applied to the results to improve the phase measurement. This filter has also been effective in reducing phase noise and before the implementation of unwrapping process (Notti et al. 2015). The resulting deformation map is presented in Figure 1, and all these steps are shown in Figure 4. The resulting deformation map provides detailed information on surface deformation for landslides and land subsidence. However, in this study, we focused on just land subsidence. For more certainty, the subsidences that occurred with a magnitude of over 0.02 metres were selected for both training and test data. Seventy percent (6654 pixels) of these areas were randomly selected as training data.



METHODOLOGY

Fuzzy inference system

A fuzzy inference system (FIS) includes expert knowledge and experience to design a process with input and output fuzzy sets that are controlled by if–then rules (Armaghani et al. 2015a). In simple terms, a FIS is a system which can obtain new knowledge from existing knowledge by using fuzzy logic (Camastra et al. 2015; Cavallaro 2015). A fuzzy inference system is made up of three sections: the first section is the fuzzification process when all crisp values are converted to a linguistic input value using a MF of the system (Tahmasebi and Hezarkhani 2012). The inference engine is the second part and is used to assess the degree of membership of input data based on the output fuzzy sets (Bui et al. 2012). Finally, the fuzzy output values are converted to crisp values in a process called defuzzification (Armaghani et al. 2015a). It can be said that the inference system can produce fuzzy output values based on inference rules as soon as it obtains fuzzy values.

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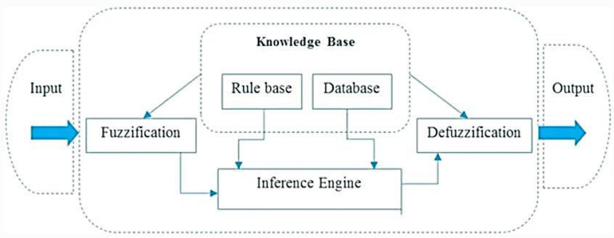

Structure of a fuzzy inference system

Generally, three main fuzzy inference systems are used in the literature: The Mamdani model, the Takagi and Sugeno (TKS) model, and the Tsukamoto model. The second model (TKS) is more common (Shabankareh and Hezarkhani 2016) and used in this study. This model renders possible to create fuzzy rules from input data. Moreover, most of the problems do not need rigid conditions in their relative factors which are introduced to the model as input data (Wang et al. 2011). The difference between the Mamdani and TKS models were explained by Cavallaro (2015). The main reason for using the Takagi and Sugeno model in this study is that it is a linear combination of inputs and has fuzzy inputs and crisp outputs (Naderloo et al. 2017). It is also a very efficient computational method for optimization as well as in terms of its implementation.

Hybrid learning algorithm

An ANN learning algorithm is used in ANFIS to set up the fuzzy inference system with determined input and output data (Tahmasebi and Hezarkhani 2012). A hybrid learning algorithm was used for training. This algorithm consists of a least-square estimator and gradient descent method (Anwer et al. 2012; Pandey and Sinha 2015). The main objective of the training is to find the optimal parameters for the fuzzy inference system with the minimum value of the error function E, which is the difference between the target amount (ti) and the output value of the model (fouti) (Bui et al. 2012).

Introducing adaptive neuro-fuzzy inference system structure

ANFIS consists of a hybrid model in which the nodes in different layers of the network provide a neural network for estimating the fuzzy parameters (Polykretis et al. 2017). This model takes advantage of both fuzzy logic and artificial neural networks and combines both approaches making the most of their respective advantages. For further explanation, part a of Fig. 4 shows a Sugeno fuzzy model with two rules of fuzzy if–then, with two input values x and y, and f as an output (Jang 1993; Armaghani et al. 2015b).

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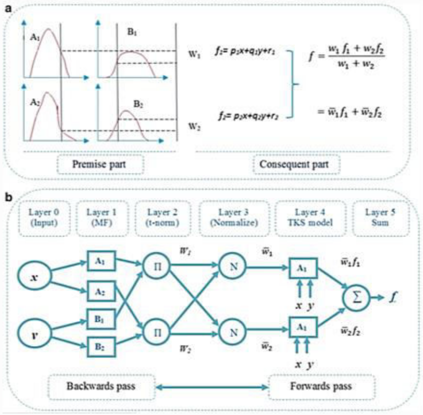
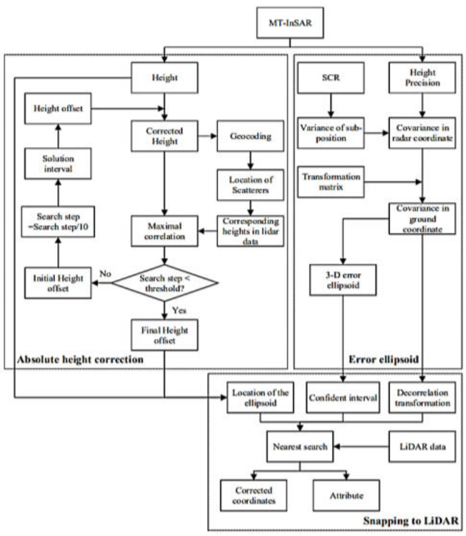


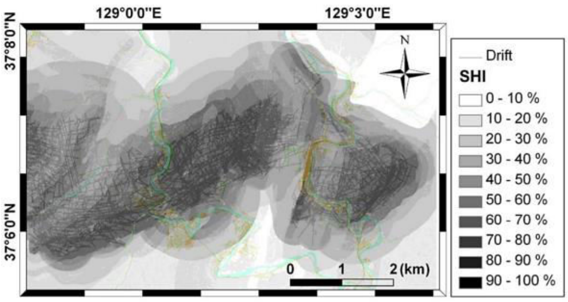
a Sugeno fuzzy model with two rules,

b typical ANFIS architecture

FLOWCHART



RESULT



CONCLUSION

The quantitative prediction of locations vulnerable to coal mine subsidence have mainly been carried out based upon field surveyed data. However, field surveys for subsidence occurrence have been limited to the residential areas and national infrastructures. This study demonstrates that the radar interferometry is a complementary tool to observe the ground subsidence in that case. This study is specifically meaningful in that a subsidence hazard map was produced by GIS analysis based on the data acquired from radar observation in the early 1990s and it was then verified by using the data observed about 15 years later. L-band SAR system was used in this study, however, there is a limitation of spatial resolution to detect the subsidence because the most coal mine subsidence in Korea occurs in small scale. So, the more high resolution of SAR, for instance X-band system is required for more practical use of remote sensing in studying coal mine subsidence. This study is expected to instigate the application of KOMPSAT-5, a Korean X-band SAR system, which is to be launched in 2010, to the detection of the ground subsidence.

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