GIS-based Subsidence Hazard Assessment around an Abandoned Coal Mine in Korea

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1. Introduction

This study is concerned with subsidence hazard mapping around abandoned coal mine in Korea, based on a geographic information systems (GIS). Toward this aim, data were entered into a spatial database using ArcGIS 9.2 software from topographic maps, borehole data, mine drift maps including sites of subsidence occurrence obtained from site investigation. From the database, eight primary factors were processed and extracted which contribute to subsidence occurrence. The correlations between subsidence events and related factors were analyzed using frequency ratio (FR) and integrated model (FR with analytic hierarchy process); subsidence hazard mapping was conducted using each model. To compare the results obtained from two models, the cumulative frequency diagram and area under the curve (AUC) technique was applied to quantitatively calculate the prediction accuracy in subsidence hazard mapping. This paper describes the details of subsidence hazard assessment implementations in support of planning abandoned coal mine management.

2. Study area

The study area is Sewon coal mine (37°12´~37°13´N, 128°53´10´´~128°54´10´´E) which is located in Jungsun-gun, Gangwon-do in South Korea. South Korea is located in East Asia, occupying the southern half of the Korean Peninsula. Figure 1 shows topographic contour lines, distribution of road and mine drift with subsidence occurrence locations in the study area.

3. Data integration

To extract and analyze factors controlling subsidence events near coal mine, a database was compiled using data obtained from topographic map at a scale of 1:5,000, borehole data and mine drift maps (1:1,200) including subsidence occurrence points (Coal Industry Promotion Board, 2005). Eight factors relevant to subsidence initiation were then extracted from the database (i.e., mine drift depth, mine drift density, distance from mine drift, slope, flow accumulation, rock mass rating, groundwater level, distance from road).

Topographic contour lines obtained from the topographic map were converted to a triangulated irregular network (TIN) model and from there a digital elevation model (DEM). DEM has a resolution of 670 rows and 140 columns, and totally 93,800 grids and cell size of subsidence and parameter maps was chosen 5m×5m. In the DEM, slope was derived using the surface analysis module and flow accumulation was calculated from the hydrology analysis function in ArcGIS 9.2 software. Line density function and Euclidean distance function were applied to mine drift (mined space or pathway to carry coals) polyline to derive mine drift density and distance from mine drift, respectively. Then, mine drift map were converted to 5m×5m raster layer and mine drift depth was calculated by subtracting mine drift height from DEM. With the 10 boreholes data on rock mass rating (RMR) and groundwater level, ordinary Kriging interpolation method was carried out to create RMR map and groundwater level map of study area. Lastly, distance from road was derived from the Euclidean distance function applied to road layer. 1,730 subsidence occurrence grids were identified among the total grids in the study area. Eight thematic maps of the study area were presented in Figure 2.

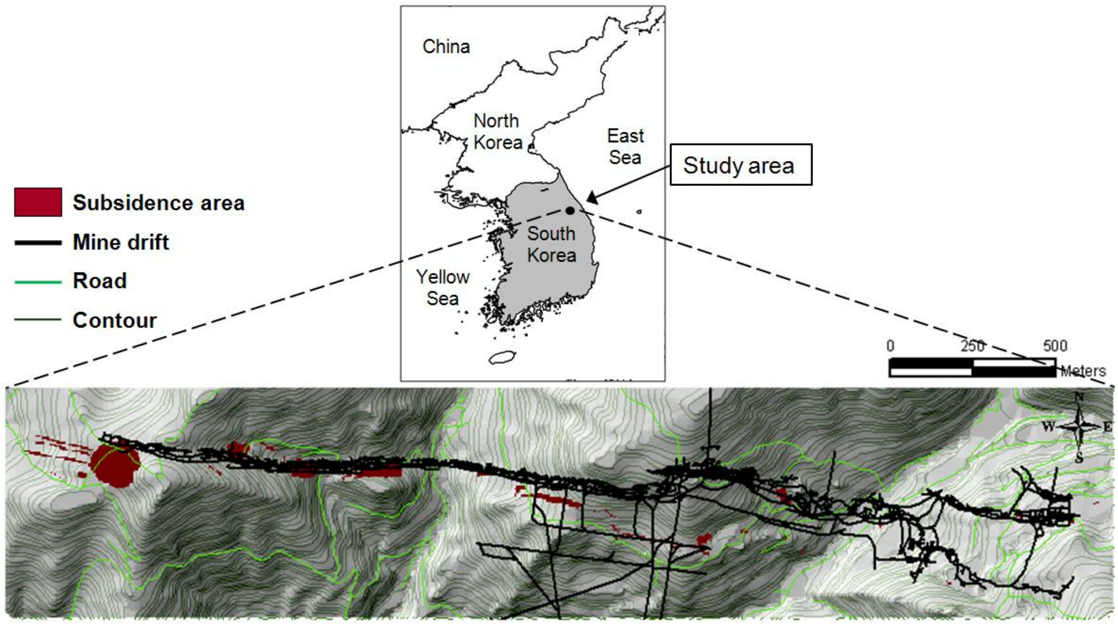

Figure 1. Mine drifts and subsidence occurrences location map of study area.

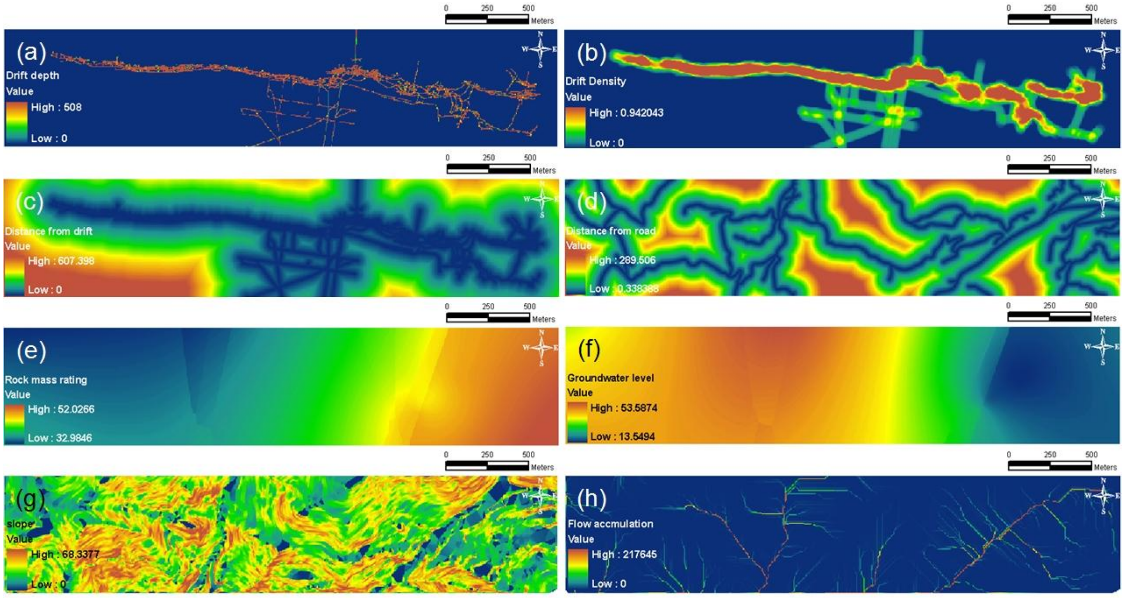

Figure 2. Thematic maps of study area.

4. Results and Discussions

4.1 Correlation between subsidence and related factors

The factors contributing to subsidence occurrence were classified to calculate the correlation between subsidence occurrence and related factors, and to apply two models to spatial data. The study area was divided into six areas to objectively identify and analyze the effect of each class or range of factors on calculation of the subsidence hazard index (SHI). Table 1 gives rating value of each class for the factor and relative weight for each factor. Detailed study process of subsidence hazard assessment using GIS is given in Figure 3.

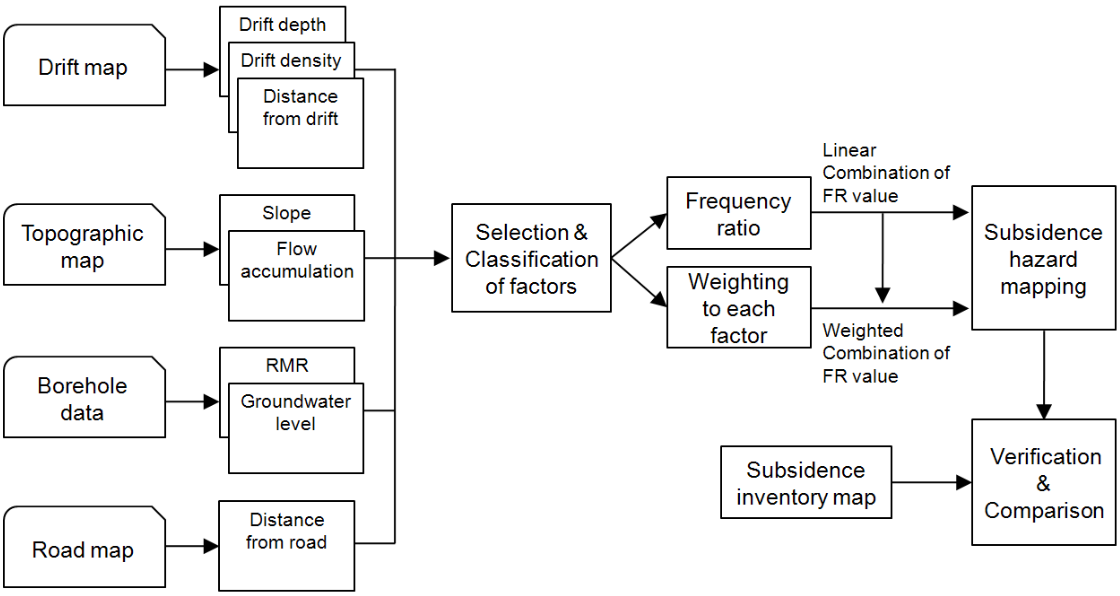

Figure 3. Procedure of subsidence hazard assessment based on GIS.

Table 1. Frequency ratio of each class and relative importance among the factors.

Factor	Class	Subsidence occurrence grids	Subsidence occurrence ratio (%)[a]	Domain grids	Domain grid ratio (%)[b]	Frequency ratio[a/b]	Relative weight
Mine drift depth (m)	0	1,425	82.37	88,502	94.35	0.87	0.2660
	0-100	81	4.68	1,706	1.82	2.57	
	100-150	105	6.07	1,476	1.57	3.86	
	150-200	45	2.60	1,002	1.07	2.44	
	200-250	40	2.31	530	0.57	4.09	
	> 250	34	1.97	584	0.62	3.16	
Mine drift density	0	656	37.92	66,612	71.01	0.53	0.2069
	0-0.1	362	20.92	13,956	14.88	1.41	
	0.1-0.2	266	15.38	5,672	6.05	2.54	
	0.2-0.3	139	8.03	2,713	2.89	2.78	
	0.3-0.4	119	6.88	2,011	2.14	3.21	
	> 0.4	188	10.87	2,836	3.02	3.59	
Distance from mine drift (m)	0-25	959	55.43	23,281	24.82	2.23	0.0862
	25-50	253	14.62	11,213	11.95	1.22	
	50-75	204	11.79	9,107	9.71	1.21	
	75-100	163	9.42	7,812	8.33	1.13	
	100-150	108	6.24	12,630	13.46	0.46	
	> 150	43	2.49	29,757	31.72	0.08	
Distance from road (m)	0-25	803	46.42	27,726	29.56	1.57	0.0542
	25-50	618	35.72	20,327	21.67	1.65	
	50-75	248	14.34	13,989	14.91	0.96	
	75-100	47	2.72	10,436	11.13	0.24	
	100-150	14	0.81	13,385	14.27	0.06	
	> 150	0	0.00	7,937	8.46	0.00	
Rock mass rating	32-35	1,336	77.23	20,119	21.45	3.60	0.1959
	35-38	128	7.40	26,866	28.64	0.26	
	38-41	88	5.09	11,657	12.43	0.41	
	41-45	136	7.86	12,901	13.75	0.57	
	45-48	19	1.10	11,335	12.08	0.09	
	> 48	23	1.33	10,922	11.64	0.11	
Groundwater level (m)	12-20	38	2.20	22,167	23.63	0.09	0.0862
	20-32	73	4.22	10,149	10.82	0.39	
	32-42	685	39.60	17,484	18.64	2.12	
	42-46	353	20.40	19,574	20.87	0.98	
	46-48	179	10.35	11,721	12.50	0.83	
	> 48	402	23.24	12,705	13.54	1.72	
Slope (˚)	0-15	444	25.66	16,178	17.25	1.49	0.0301
	15-20	664	38.38	16,089	17.15	2.24	
	20-25	341	19.71	18,532	19.76	1.00	
	25-30	144	8.32	18,809	20.05	0.42	
	30-35	107	6.18	14,428	15.38	0.40	
	> 35	30	1.73	9,764	10.41	0.17	
Flow accumulation	0-10	217	12.54	12,843	13.69	0.92	0.0745
	10-30	362	20.92	20,952	22.34	0.94	
	30-50	258	14.91	14,441	15.40	0.97	
	50-100	345	19.94	20,366	21.71	0.92	
	100-500	392	22.66	19,278	20.55	1.10	
	> 500	156	9.02	5,920	6.31	1.43	

For the cases of mine drift density and flow accumulation, the calculated FRs increase with increasing value of each class, which means that the probability of subsidence occurrence increases with increasing value of each parameter. In case of distance from mine drift and distance from road factors, the probability of subsidence occurrence increases with decreasing value of each parameter. Mine drift depth parameter showed the highest weight among the factors, followed by distance from mine drift and RMR factor. Expert judgment indicated that slope of relief factor and distance from road factor had a relatively minor influence on subsidence occurrence.

4.2 Subsidence hazard mapping

Based on the results in Table 1, the FRs for the each class of eight factors calculated and summed to compute a SHI (1). Also, calculated FRs were combined with the weightings for each factor derived using analytic hierarchy Process (AHP) method, the eight values were combined to determine the SHI (2).

$$SHI = \sum_{n=1}^{8} FR \tag{1}$$

$$SHI = \sum_{n=1}^{8} (FR \times Weight) \tag{2}$$

Figure 4 describes subsidence hazard mapping results of the study area using different models. Regions with high SHI (red coloured) have high subsidence potential, so SHI value can be used as a criterion with which to rank areas in terms of subsidence hazard. Most of the regions along the mine drifts are susceptible to subsidence and left-upper part of study area showed high SHI due to bad quality of base rocks.

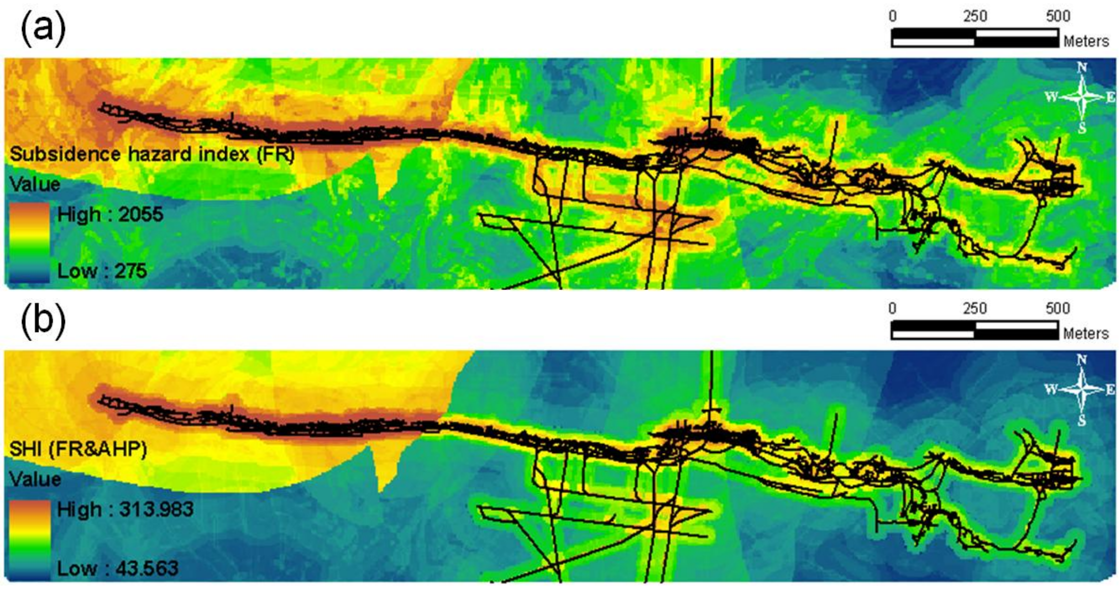

Figure 4. Subsidence hazard mapping of the study area.

4.3 Verification of subsidence hazards predictions

To verify the prediction accuracy of the results, subsidence hazard maps were compared with the locations of past subsidence. To quantitatively assess and compare the results of different models, area under the curve (AUC) technique was used (Figure 5). AUC assess the subsidence prediction performance of models by using 100 subdivisions (at 1% intervals) of SHI values for all grids in the study area sorted in descending order (x-axis) and the cumulative percentage of subsidence occurrence in the classes (y-axis); cumulative frequency curves were drawn to calculate AUC

(Yilmaz 2009). Finally, the accuracy in predicting subsidence occurrence is indicated by the ratio of AUC to the total area.

Figure 5 illustrates cumulative frequency diagram for two models applied in this study. According to the results of AUC analysis, the FR model yielded an area ratio of 0.897, corresponding to a prediction accuracy of 89.7% which showing better accuracy than that of integrated model.

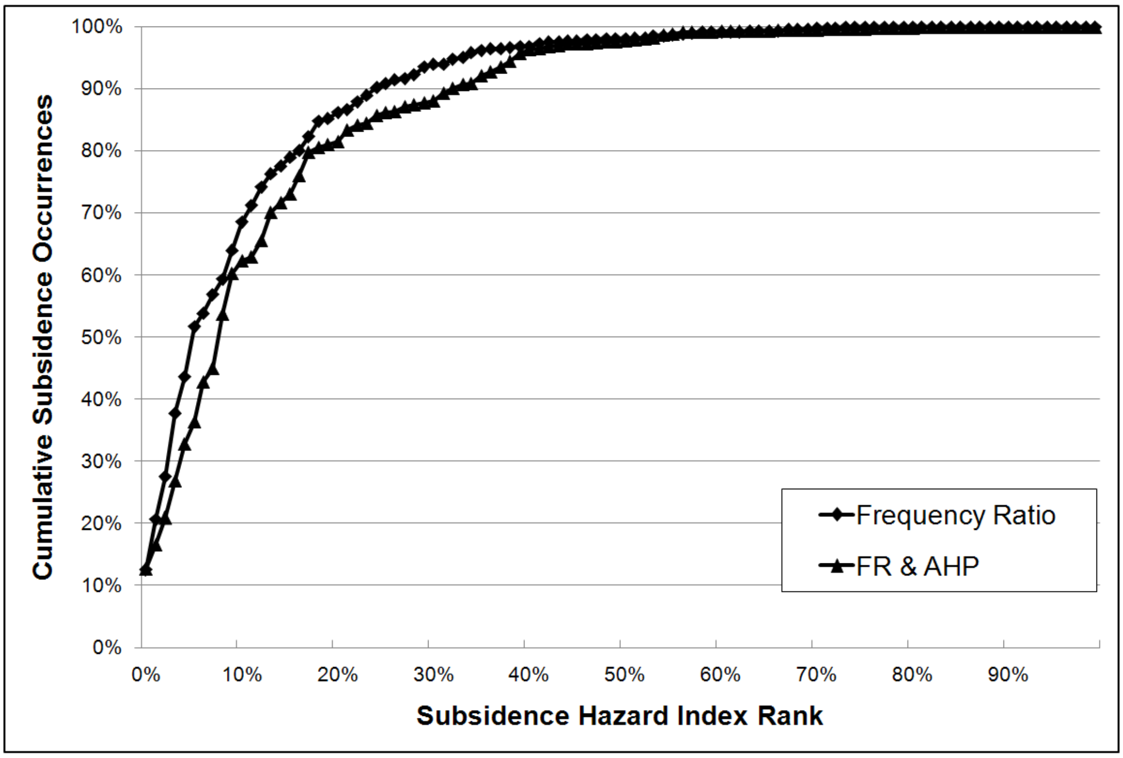

Figure 5. Cumulative frequency diagrams for verification of applied models.

5. Concluding remarks

In this study, subsidence hazard assessment using GIS was implemented. Based on the statistical method combined with expert system, spatial data was stored, extracted, manipulated, visualized in GIS environment to evaluate subsidence hazard in abandoned coal mine. The results obtained in this paper can be used as basic data to assist subsidence hazard management and land use planning in mine area.

Acknowledgements

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