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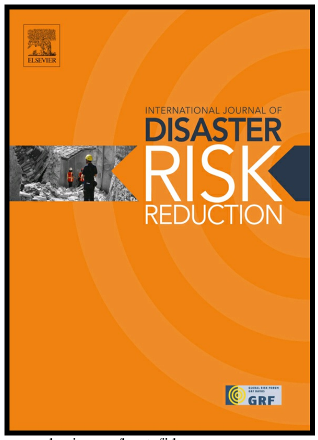

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Chemical Accident Hazard Assessment by Spatial Analysis of Chemical Factories and Accident Records in South Korea

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Abstract

This study identified the potential chemical accident occurrence in Korea by analyzing the spatial distribution of chemical factories and accidents. The number of chemical factories and accidents in 25-km^2 grids were used as the attribute value for spatial analysis. First, semi-variograms were conducted to examine spatial distribution patterns and to identify spatial autocorrelation of chemical factories and accidents. Semi-variograms explained that the spatial distribution of chemical factories and accidents were spatially autocorrelated. Second, the results of the semi-variograms were used in Ordinary Kriging to estimate chemical hazard levels. The level values were extracted from the Ordinary Kriging result and their spatial similarity was examined by juxtaposing the two values with respect to their location. Six peaks were identified in both the factory hazard and accident hazard estimation result, and the peaks correlated with major cities in Korea. Third, the estimated two hazard levels were classified with geometrical interval and could be classified into four quadrants: Low Factory and Low Accident (LFLA), High Factory and Low Accident (HFLA), Low Factory and High Accident(LFHA), and High Factory and High Accident (HFHA). The 4 groups identified different chemical safety management issues in Korea; safe LFLA group, many chemical reseller factories were found in HFLA group, chemical transportation accidents were in the LFHA group, and an abundance of factories and accidents were in the HFHA group. Each quadrant represented different safety management obstacles in Korea, and studying spatial differences can support the establishment of an efficient risk management plan.

Key words: chemical accident, hazard, spatial analysis, safety management, classification

1. Introduction

Chemical materials have been used in agricultural, manufacturing, engineering, and other various industries, and the demand for chemical use is continually increasing [1]. In 1942, a mere 600 000 chemical compounds had been identified. In 1947, this number had increased to 4 million, and since then the total number of identified chemical compounds has risen to around 11 million [2]. Advancement of the chemical industry required complex systems of production, transportation, and storage, so the possibility of a chemical accident occurring and the severity of possible accidents increased [3]. As a result, many severe chemical accidents in recent history have affected the environment and human population. The Indian Bhopal accident in 1984 [4], Italian Seveso accident in 1976 [5], and Fukushima nuclear disaster in 2011 [6] had severe consequences for both the environment and human population. To combat the growing risks of chemical accidents, the United Sates established the National Atmospheric Release Advisory Center (NARAC) [7] and the European Union introduced the Registration, Evaluation, and Authorization of Chemicals (REACH) to systematically reduce chemical exposure [8].

According to the European Environment Agency [9], chemical accident management requires further studies in estimating the potential scale of their effects, their unpredictability, and the uncertainties of their consequences for Environmental Risk Assessment (ERA). ERA appeared to be challenging, due to a lack of related data and the complexity of the environment, and traditionally, results from ERA are presented in a non-spatial manner [10]. Chemical accidents were statistically analyzed and the most dangerous chemical materials in use were identified by comparing the number of accidents, injuries, and damages [11]. General statistical analysis had many limitations in studying chemical accidents properly because chemical accidents have spatial distribution [12].

The development of Geographic Information Systems (GIS) has greatly improved spatial representation and spatial analysis of all forms of information and data. Spatial statistical analysis can explain the distribution and pattern of spatial data based on the theory that "everything is related to everything else, but near things are more related than distant things" [13]. Spatial statistical analysis has been applied to various academic fields, including ecology [14], epidemiology [15], urban planning [16], and chemical risk management [17]. Furthermore, development of GIS technology enhanced regional level of ERA studies for example lead risk of soil in Blackwattle Bay region [18] and chemical accident risk assessment with exposure model in Nanjing chemical Industry Park [19]. Instead of abundance of the study, studies that apply spatial statistical analysis to chemical factories and accident locations from a safety management perspective for national scale were difficult to find. In forestry, spatial analysis was used to understand the occurrence patterns of forest fires, and an efficient accident management plan was suggested [20]. In chemical industry, spatial analysis could be very powerful tool for safety management.

Previous studies have used different spatial analysis methods to assess chemical hazard, and they were categorized into 4 groups. The first group estimated risk from the measured chemical substance level at the sample site and used spatial analysis to estimate the level of chemical risk in the area [10,20,21,22,23]. The second group developed indices by calculating the index using existing data or geographic properties [23,24]. The third group used a model and scenario to predict chemical material dispersion in space [25,26,27]. The fourth group used remote sensing techniques and observed damage changes in space and time [28,29,30] This study falls into the first and the second groups, because chemical hazard levels were estimated by spatial analysis, and the estimated values were systematically classified into four classes that indicate areas with potential future accident. This study applied spatial statistical analysis on location of chemical factories and accidents to understand the spatial distribution patterns of the two variables, estimated two different hazard levels, and finally to classify levels into 4 groups to provide useful information for management purposes.

2. Methodology

2.1. Data description

2.1.1. Definition of Hazard and Occurrence

Hazard and risk are often confused in their use, and many articles define the meaning of the two words to prevent misuse [19,31]. In this article, the definitions of hazard was carefully selected from previous studies to avoid the misuse word with risk. From reviewing literature, it is appropriate to consider the number of chemical factory and accident in a grid cell as the hazard.

The simple definition of hazard is “a potential damage” [32]. Following the definition of a hazard, chemical factories are potential damage source, where accidents can occur. Further definition of a hazard includes intensive property [33], which illustrates the influence of the chemical material, and chemical toxicity is usually a good example of this. Furthermore, definition of hazard includes the possibility of potential accidental pollution. Chemical accident records has probability since the accident had occurred. Number of the chemical factories and chemical accident in a grid cell also act as an intensive property and source of the danger, because area with high number of chemical factories and accident can expect higher hazard level. Occurrence means outbreak of phenomenon or incident. In this article, occurrence means the potential future accidents that might appear in estimated hazardous area. The previously occurred chemical accidents were used as the input data for the estimation.

2.1.2. Study Area: South Korea

Korea is ranked 6th in the world in chemical industry market shares and accounts for 3.4% (138.7 billion USD) of the world's chemical market (4.1 trillion USD), behind China (21.9%, 903.4 billion USD), the US (17.5%, 720.0 billion USD), Japan (8.2%, 338.2 billion USD), Germany (5.5%, 228.8 billion USD), and Brazil (3.6%, 149.6 billion USD) [34]. The number of domestic chemical manufacturers registered in Korea in 2002 was 12,205, and increased to 16,547 in 2010. According to the Hazardous Chemical Material Accident Casebook, the total amount of chemical material usage in Korea rose from 21,159 to 32,294 tons (52.6%), and the number of chemical accidents rose from 26 to 70 (169.2%) between 2001 and 2006 [35].

The estimated economic loss from chemical industrial accidents is estimated to be up to 15 trillion KRW (16.9 billion USD), and the number of victims of chemical accidents exceeded 2,900 in 2012 [36].

The United Nations Environment Programme (UNEP) has emphasized the necessity of reducing the risk of the chemical industry [37], and the 2012 Gumi hydrogen fluoride leaking accident in southeast chemical industry complex in South Korea increased the public awareness of chemical accidents' potential to cause severe harm to people, the environment, and the economy.

The Toxic Chemicals Control Act (TCCA) was enacted in 1992, and the Korea Ministry of Environment (MOE) has been responsible for managing toxic chemicals [38]. In 2015, the Chemical Material Management Act (CMMA) and Chemical Material Assessment Act (CMAA) were enacted after amending the TCCA. Furthermore, the CMAA included new clauses, such as environmental impact assessment, immediate reporting duty of accidents, business licensing, and the designation of a special management area to improve preparedness and responses to chemical accidents [39].

2.1.3. Materials: Chemical Factory and Chemical Accident Data

Chemical factory data was provided by the MOE. There are 4,916 factories included in this data, and the chemical factory data includes detailed information about factories, like title, business registration code, owner, address, phone number, chemical materials, amount of them used, and chemical states.

Chemical accident data was provided by the National Institute of Chemical Safety under MOE. The agency established the online Chemical Safety Cleaning House (CSC) System, which provides chemical accident records to the public [40]. At the beginning of the research, the system provided chemical accident data from 2006 to 2015, and total number of accidents was 418. The average annual accident outbreaks from 2003 to 2012 was 13.3 cases, but after 2012 it increased to 97.7 cases. This phenomenon is considered to be influenced by people's awareness of chemical accidents following the Gumi accident which encourage them to report even small accidents [41].

Chemical factory and accident data were geocoded based on their address and projected as point data on ArcGIS. The spatial distribution of the two data sets are described in Figure 1.

The chemical accident data for this study had 126 cases of damages to humans by accidents and only 14 cases resulting in economic loss. The numbers of cases were insufficient for spatial analysis and, regarding that even one chemical accident can cause severe damage [42], this study focused on occurrence of chemical accidents rather than their magnitude.

Point data has two major characteristics: the first is the density of the point in each space, and the second is spatial dependence or spatial autocorrelation, which is measured from values and distance between the points [43,44]. Both density and spatial autocorrelation is important in understanding the spatial patterns of chemical accidents and factories. The density of points was measured by counting the numbers of factories and accidents in the 25-km^2 grids, and spatial autocorrelation was measured by a semi-variogram.

<Figure 1>

2.2. Research Method

2.2.1. Spatial Autocorrelation of Chemical Factories and Accidents

The chemical factories and accident numbers in the 25-km^2 grids have replaced the attribute value for the spatial analysis. Hazard assessment of chemical factories and accidents can be assessed with statistical analysis but it has many limitations [45]. For instance, prospecting required geostatistical analysis because statistical analysis can only estimate amount of mineral but where they are buried. Spatial analysis of Chemical factory and accident can quantify the hazard level in unknown area.

Understanding spatial distribution pattern of chemical factories and accident is prerequisite before the hazard assessment. Spatial autocorrelation describes the similarity of spatial entities increases with close spatial location [46] and it can be quantified by Semi-variogram, Correlogram, Covariacne, and Madogram [45]. In this study Semi-variogram was chosen to determine spatial dependence of chemical factories and accident through geostatistics[47,48,49] before the estimation of the hazard level. The experimental Semi-variogram was estimated by equation 1:

$$\gamma(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [z(u_\alpha + h) - z(u_\alpha)]^2 \quad (1)$$

u_α represents spatial location of the chemical factories and accidents were translated to longitude and latitude. $z(u_\alpha)$ is the attribute value of data located at u_α, and in this study the attribute values were the number of chemical factories and accidents in a grid. $z(u_\alpha + h)$ is attribute value of data that was located away from u_α, with h as distance and n as the number of the pairs of points in lag size [41]. Semi-variogram gives the square of the difference between the attribute values of the two grids. When the two grids have similar number of chemical factory in short lag distance, the variance will be low and it estimates a high spatial autocorrelation of the chemical factory, and same for the chemical accidents. Additionally, lag size means maximum allowed distance to observe comparative point and lag distance refers actual distance difference of point to points within the lag size.

After investigating spatial dependency with the experimental semi-variogram, a theoretical semi-variogram model should be used to describe the spatial autocorrelation as a graph [51]. In this study, an exponential model was selected because both chemical factories and chemical accident numbers in grids showed exponential growth, and Root Mean Square Error (RMSE) was the lowest with this model. Exponential (Equation 2) models were fitted to the scaled experimental semi-variograms,

$$\gamma(h) = C_0 + C_1[1 - exp(-\frac{3h}{a})], h \geq 0 \quad (2)$$

Where C_0 is the nugget effect; $C_0 + C_1$ is sill; h is the distance between experimental observations; and α is spatial dependence range [52]. Nugget effect occurs when two points have difference with zero separation distance and sill means variance value when model attains the range. The semi-variogram model levels out at a certain distance, and the distance at which the model first flattens out is the range. Distances further than the range are not spatially autocorrelated, whereas distances before the range are spatially autocorrelated [53]. Where the semi-variogram model attains range, the y-axis value is called the sill and it shows the variance of the data [54]. The partial sill is the sill subtracted from the nugget, and a high partial sill means high changes in spatial distribution [54,55].

After, the experimental and theoretical Semi-variogram, the spatial dependency of the chemical factories and accident in 25-km^2 grid is quantified to show the distribution patterns of the two variables, and the result of Semi-variogram allowed the study to proceed hazard level estimation.

2.2.2. Hazard Estimation from Chemical Factories and Accidents

Hazards from chemical factories and chemical accidents were estimated using the analysis result of the semi-variogram and Kriging interpolation method. Kriging is a geostatistical interpolation method which estimates an unknown value in an unknown location [56,57]. In this study, the Ordinary Kriging method was selected to prevent estimation bias and minimize error variance [51].

At the unknown location u, Ordinary Kriging estimates $z^*_{OK}(u)$ by linear summation of a nearby observed value $z(u_\alpha)$ as in equation (3) [58]:

$$z^*_{OK}(u) = \sum_{\alpha=1}^{n(u)} \lambda_\alpha^{OK}(u) z(u_\alpha) \tag{3}$$

In equation (3), weight λ_α^{OK} must be decided while minimizing estimation distribution $\mathrm{VAR}\{z^*_{OK}(u) - z(u)\}$ and satisfying a non-biased condition $\mathrm{E}\{Z^*_{OK}(u) - Z(u)\} = 0$. To satisfy the condition, Ordinary Kriging uses equation (4) [58,59].

$$\left\{ \begin{array}{l} \sum_{\beta=1}^{n(u)} \lambda_\beta^{OK}(u) = \gamma(u_\alpha - u_\beta) - \mu_{OK}(u) = \gamma(u_\alpha - u)\alpha = 1,\ldots,n(u) \\ \sum_{\beta=1}^{n(u)} \lambda_\beta^{OK}(u) = 1 \end{array} \right\} \tag{4}$$

In equation (4), $\mu_{OK}(u)$ and $\gamma(u_\alpha - u_\beta)$ represent the Lagrangian parameter and variogram value with distance between two points. The Kriging estimation value $z^*_{OK}(u)$ and estimation variance in equation (5) are calculated from Ordinary Kriging.

$$\delta_{OK}^{2}(u) = \sum_{\alpha=1}^{n(u)} \lambda_{\alpha}^{OK}(u)\gamma\left(u_{\alpha} - u_{\beta}\right) - \mu_{OK}(u) \quad (5)$$

Hazard values from chemical factories and accidents occurrence were estimated from Ordinary Kriging and all values were used to gain identification numbers respective to their spatial location in Korea. Estimated hazard values were arranged by identification number to visualize hazards change by location. Firstly, the two hazard estimation results values were visualized on a scatter plot and the distribution of values was observed, and secondly, Pearson Product Moment Correlations were conducted to measure the statistical relationships between hazard estimated value of chemical factories and chemical accidents.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^{2} - (\sum x)^{2}][n\sum y^{2} - (\sum y)^{2}}} \quad (6)$$

Where x and y is the estimated hazard of factories and accidents values from Ordinary Kriging and n is number of values. The correlation coefficient (r) can vary from -1 to 1. An r = 0 means that there is no connection between the two measures at all, and an r = 1 means that the two measures are positively correlated, with both moving in the same direction. An r = -1 also means that the two measures are negatively correlated, with both are moving in opposite directions. Values from -0.5 to -1 or from .5 to 1 are considered high [60].

2.2.3. Hazards Classification by Geometrical Interval

The objective of classification is to group data in such a manner so that the observations within a class similar, but also the classes themselves are dissimilar. Geometric interval is a mathematically defined interval system, producing class boundaries and intervening distances that change systematically, and this method creates class breaks based on class intervals that have a geometrical series [61].

$$a, ar^2, ar^3, \ldots ar^{n-L} \quad (7)$$

Equation 7 shows how geometric interval produces class boundaries, where a is the first term, r is the common ratio, n is the number of terms and L is the last term, ar^{n-L} [61]. As the equation is formulated, geometric interval is only a useful method when the data has geometrical series, an exponential function. The number of chemical factories and accidents in grids, and estimated hazard values of chemical factories and accidents from Ordinary Kriging, had geometrical series.

In this study, estimated hazards were classified through two processes. First, the result of estimated hazards were classified with geometrical intervals into three groups (low, medium, and high). Due to a large number of zero values, the first result of geometrical interval had four groups (very low, low, medium, and high) but the very low and low levels were aggregated under low level.

Second, hazard levels were classified together. The hazard values were arranged by their identification number, and computed in a graph with hazard of factories as the dependent variable and hazard of accidents as the independent variable. For the next step, hazard of chemical factories and accidents were classified into high hazard and low hazard. Each axis was divided into two groups, with their break values assigned from the geometrical interval, thereby creating a quadrant. Quadrant I is HFHA: High Factory and High Accident, quadrant II is LFHA: Low Factory and High Accident, quadrant III is LFLA: Low Factory and Low Accident, and quadrant IV is HFLA: High Factory and Low Accident.

For the overview of the hazard assessment, firstly the spatial distribution of chemical factories and accident occurrence were examined by Semi-variogram, secondly the result of Semi-variogram and Ordinary Kriging estimated the hazard level for factories and accidents of South Korea, thirdly the estimation values were classified by geometrical interval. Finally, the results were produced as chemical factory hazard map, chemical accident hazard map, and together, potential chemical hazard occurrence map.

2.2.4. Verification of Estimated Hazard and Risk

The Ordinary Kriging of chemical factories and accident records estimated hazard and risk values in Korea. These estimated values were classified by geometrical intervals and divided into three groups: low, medium, and high. The results of the Ordinary Kriging and geometrical interval classification were verified by overlaying the actual accident records over the classification results.

Verification of estimated risk used less verification data than hazard, because accident data from 2003 to 2015 were used to estimate risk. Estimated hazard was verified using data from 2003 to 2015, 2016 to 2017 and 2003 to 2017 accident records. For verification, actual accidents were plotted on the map and allocated into three levels of hazard and risk (high, medium, low), dependent on their location. After this, the number of accidents in each level were divided by the level's area to calculate accident density, because high hazard/risk area is much smaller than low hazard/risk area (equation 8). Where D(L) is the density of the level area, L(n) is the number of accidents in the level area, and L(a) is the area of the level. Verification was conducted on entirety of Korea, and different cities of Korea, where hazard and risk values are significantly higher.

$$D(L) = \frac{L(n)}{L(a)} \quad (8)$$

The same method was used to verify the classification of integrated hazard and risk results. The numbers of chemical accidents in 4 groups (LFLA, HFLA, LFHA, and HFHA) were counted and chemical accident density was calculated for comparing groups. Additionally, the number of factories in the 4 groups was used to verify both of hazard and risk together.

3. Results

3.1. Spatial Autocorrelation of Chemical Factories and Accidents

The semi-variogram of the number of chemical factories and accidents in girds is shown Figure 2. Spatial autocorrelation was examined in both the chemical factories and accidents semi-variogram results (Figure 2). The autocorrelation result was interpreted with 4 components: range, sill, partial sill, and nugget. The chemical factory range was 12.1 km, and the chemical accident range was 7.53 km therefore chemical factory had autocorrelation in larger area. The semi-variogram had the same values for partial sill and sill due to the no nugget effect which illustrate no significant error in data. The chemical factory's partial sill was 57.3 and chemical accident partial sill was 0.286 which can illustrate high variance of chemical accident with distance. The existence of spatial autocorrelation means that the chemical factories and accidents are not randomly distributed in space, but have a kind of clustering tendency.

<Figure 2>

3.2. Hazard Estimation from Chemical Factories and Accidents

Distribution of the Ordinary Kriging result were examined to validate geometrical interval as the proper classification method and estimated hazard values for chemical factories and accidents had exponential increments which makes geometrical interval a proper classification method (Figure 3).

Figure 4 depicts two hazard maps from the chemical factories (a) and chemical accidents (b) by Ordinary Kriging. Factory hazard and accident hazard values were extracted as point data and arranged by their identification number. The results showed 6 peaks in both maps (Figure 5). The peaks were matched with the administrative districts of Korea, and the cities with high peaks were the capital region, Daejeon city, Daegu city, Ulsan city, Busan city, and Yeosu city.

The hazard value sets, arranged by identification number, were juxtaposed on the graph for comparison and the peaks in two different graphs were very similar. The highest hazard level from both factories and accidents were identified in the capital region, and Ulsan, Busan, and Yeosu cities.

Additionally, Pearson correlation was used to examine similarity between two hazard variables. The resulting R value was 0.706, with a P value of less than 0.01.

<Figure 3>
<Figure 4>
<Figure 5>

3.3. Hazard and Risk Classification by Geometrical Interval

The result of applying the geometrical interval created break values for factory and accident hazard, which classified the data into four quadrants, and the break value was 0.058, 0.41 for the x, y-coordinate. The points located on the right side of the break values were considered as high hazard, and the points located above the break values were considered as high risk.

The four classified quadrants had distinctive characteristics in their range and data amount. Each quadrants' area and number of points were noted to understand differences in distribution patterns of the classification results. For area, quadrant I(HFHA) composed 97.2% of the total area in the graph and quadrants IV(HFLA), II(LFHA), and III(LFLA) composed 2.64%, 0.17%, and 0.0046% of the area. In contrast to the result of area, quadrant III(LFLA) had the most points in the smallest area, containing 61.6% of the total number of points, while only 6.52% of total points were found in quadrant I(HFHA). Additionally, 31.5% of points were in quadrant IV(HFLA) and only 0.40% of points were in quadrant II(LFHA). According to this observation, quadrants I(HFHA) and II(LFHA) had low point data density while quadrants III(LFLA) and IV(HFLA) had high point data density (Figure 6).

The four quadrants reflect different regions of factory and accident hazard level in Korea. Quadrant I was where both factory and accident were high(HFHA), reflecting chemical accidents that occurred in factories; quadrant II was where only accident was high(LFHA), reflecting chemical accidents during transportation; quadrant III was where both factory and accident were low(LFLA), reflecting no chemical factories and accidents; quadrant IV was where only factory was high(HFLA) reflecting factories with no accidents, but that could be considered as potential chemical accident location.

The results of classification were applied on the map by matching the point identification number to the pixel identification number. The map created from the classification not only visualized the hazard and risk level differences in space, but also provided information on where future chemical accidents were more likely to occur, therefore, the map designates the potential chemical hazard occurrence in future (Figure 7). A large area of HFHA was observed in big cities, and the capital region had the largest area. Significantly large HFHA areas were identified in major cities such as Busan, Daegu, Daejeon, Ulsan, Yeosu cities. LFHA areas were distributed evenly throughout Korea because this class represents accidents during transportation. LFLA areas were mostly found in the northeast and southwest areas of Korea, due to the small numbers of factories, but unlike the northeast, a cluster of HFHA was found in the southwest. HFLA areas were mostly found near the HFHA areas, since the location of chemical factories is restricted by the government (Figure 7).

<Figure 6>
<Figure 7>

3.4. Verification

The prediction accuracy of the chemical factory hazard map was verified by overlaying the actual chemical accident records from 2003 to 2015, 2016 to 2017 and 2003 to 2017(Table 1). National wide, the results of hazard map verification showed that 83.7% of accident density percentage in an estimated high hazard area, 15.4% in a medium hazard area, and just 0.9% in a low hazard area in Korea from 2003 to 2015. The 2016 to 2017 chemical accident data was acquired after the study had proceeded, and this data was used to verify the accuracy of the estimated hazard map. The accident density percentages were 87.8%, 11.0% and 1.1%, from high to low hazard areas from 2016 to 2017. Overall, 84.4%, 14.6%, and 0.9% of density percentages were observed from 2013 to 2017. Hazard verification was not only conducted on a national scale, but also 6 chemical industrialized cities (the capital region, Busan city, Daegu city, Ulsan city, Yeosu city) were selected for regional scale verification, and the results were similar to the national scale. Chemical accident hazard map was verified by the same method, but only 2016 to 2017 accident data was used because the chemical accident data from 2003 to 2015 was the input data for hazard estimation. The result of hazard map from chemical accident verification was similar to the result of hazard map verification of factories, and higher prediction accuracy was observed in the high hazard areas (Table 1).

<Table 1>

Also, the potential chemical hazard occurrence map was verified by applying the same verification method but this verification had four classes rather than three (low, medium, and high), and chemical factories locations were additionally overlaid as another data set for verification, since the potential chemical hazard occurrence map included both chemical hazards from factories and accidents (Table 2).

Firstly, the results of verification with the chemical accident record showed a similar result to the previous verification of hazard and risk maps. Most chemical accidents appeared in areas where both factory hazard and accident hazard were high. For instance, 379 chemical accidents out of 418 were observed in HFHA areas between 2013 to 2015. Considering area size differences among the four classes, the calculated density percentage of HFHA meant it was still the highest density percentage class (77.5%). Busan, Daegu, Daejeon, Ulsan cities' chemical accidents only appeared in HFHA areas, and the Capital region had 157 out of 160 accidents with a density percentage of 86.3%. The verification results from 2016 to 2017 and 2013 to 2017 also showed similar results to the previous verification results, and most chemical accidents were found in HFHA areas. Secondly, the number of chemical factories in each class was examined, and the majority of chemical factories are located in HFHA regions, but a high number of chemical factories were found in HFLA areas, reflecting the chemical factories without any chemical accidents (Table 2).

<Table 2>

4. Discussion

4.1. Spatial Analysis and Chemical Hazard Assessment

Many chemical factories use more than one chemical material under various concentrations, and even synthesize chemicals during the process. The possibility of a chemical accident outbreak in a factory can be deduced from the total failure rate of factories' facilities and human factors, but it requires a precise survey on entire work-place [62]. For these reasons, applying previous hazard estimation methodology was very resource and time intensive when applying national scale investment. Currently the Korean government obtains information of each factories' chemical materials and their facilities under CMMA. The publication of the data from CMMA may provide enough information to calculate the hazard level and accident probability for each factory, which can increase the accuracy of spatial analyses of hazard estimation.

This study can be improved by adding temporal factors into the spatial analysis and examining the changes of chemical hazard with time. For spatial temporal analysis, a complement of chemical accident data is necessary because one chemical accident in a year is not enough to proceed with spatial analysis. The integration of chemical accident data from reliable sources can improve the study and potentially allow researchers to conduct spatial-temporal analysis of chemical hazards and potential accident location. Furthermore on data, magnitude of the factories and accidents are dubious. For instance, chemical amount, death, and financial loss were mostly zero for all the records which was an obstacle for environmental risk assessment. Another limitation is that the study did not consider the factors or geographical condition of the area. Only the number of chemical factories and accidents were used as hazard indicators because information was limited. In future studies, other factors, such as obsolete equipment, chemical materials, elevation, and slope of the area, could be introduced for improvement of models.

Though there are many limitations of the study, it has a distinctive feature; the number of chemical factories and chemical accidents in the 25-km^2 grid were used as attribute values for spatial analysis to estimate hazard and risk. This methodology can be applied on a national scale risk assessment, which is usually challenging with other methods. The result of the spatial analysis described the spatial distribution of hazard and risk levels, which could be used for the safety management system.

4.2. Classification of Chemical Hazard

The geometrical interval classified integrated factory hazard and accident hazard into four groups (LFLA, LFHA, HFLA, and HFHA) and identified the spatial location and area of each group. The four groups represent different hazard levels in areas and illustrates the potential chemical hazard occurrence in future, therefore the safety management plan should be tailored dependent on their group.

The absence of chemical factories and accidents suggests that LFLA is the safest group, where a site management plan seems unnecessary. LFHA group also had no chemical factories, but the risk level was high in the area because of a chemical accident during transportation. The accident during transportation was ranked as the third chemical accident cause [35], and it is difficult to predict where chemical accidents are going to occur because they are mobile, unlike chemical factories. Singapore, Canada, the United States, European Union, and England have established a chemical transportation accident management system [63,64]. In Korea, the Ministry of Land, Infrastructure, and Transportation had embarked on a project on tracking chemical material transportation vehicles in 2015, but only reached the testing level [65]. Installation of safety equipment near roads in the LFHA area is a possible solution for managing transportation accidents until a proper management system is introduced.

The verification result showed that 84% of new chemical accidents between 2016 and 2017 occurred in the high risk area, where previous accidents have taken place. This skewed accident occurrence with evenly distributed chemical factories in HFLA and HFHA, and was irrational so the input data was rescanned and it was identified that the chemical factories in HFLA areas are involved with selling and transporting chemical substances, whereas factories in HFHA areas are involved with synthesizing chemicals and manufacturing chemical goods. Furthermore, HFHA and HFLA areas were clustered on the map because the Korean government restricts land use, especially under the Harmful Chemical Substance Management Act, under which the construction of chemical factories is strictly restricted by their type of business [66].

The four groups were ranked by their danger level from a safety management perspective, and HFHA was ranked as the most dangerous group due to frequent accident outbreaks requiring much management effort, and LFLA was ranked as the safest group because of the absence of both chemical factories and accidents. HFLA was considered a safer group compared to LFHA because though HFLA areas contain factories where potential accidents might occur in the future, the accidents in HFLA areas can be managed under the current system. Alternatively, chemical accidents in LFHA areas are hard to predict, yet there is no proper management system.

Limitations of hazard classification remained as high prediction uncertainties of LFHA group, accident from transportation; and simplified the hazard groups by four while BASF risk Matrix identifies 20 groups [67]. These limitations can be overcome with data supplementation, and the study is still meaningful because previous methods, such as the BASF risk Matrix, were intended to assess risks in a specific factory, whereas this study assessed hazard levels on a national scale.

5. Conclusion

In this study, chemical hazard in Korea was estimated by spatial analysis of number of chemical factories and accidents. The values were extracted from the spatial analysis result and their spatial similarity was examined by juxtaposing the two values with respect to their location.

The 4 groups were identified and they represent different chemical safety management issues in Korea; a safe LFLA group, many chemical reseller factories were found in HFLA group, chemical transportation accidents were in the LFHA group, and an abundance of factories and accidents were in the HFHA group. Spatial temporal analysis could have been conducted to present hazard and risk changes respective to time, which can identify vulnerable seasons or periods of chemical accidents. There is not yet enough data for spatial temporal analysis. A limitation of classification was the over simplification of hazard and risk classifications, but a national scale safety assessment is still a meaningful result.

Distinctive features of this study include a methodology that estimates chemical hazards through spatial analysis of chemical factories and accident densities, and classified areas with different chemical hazard occurrence in future. Founding of this study can be applied to safety management by suggesting different management plans for each group and increase the efficiency in chemical safety management systems. In future studies, geographic factors can be applied to increase the accuracy of the result, and the application of new factors could identify the risk from chemical transportation accidents, which the current classification method could not estimate.

6. Acknowledgement

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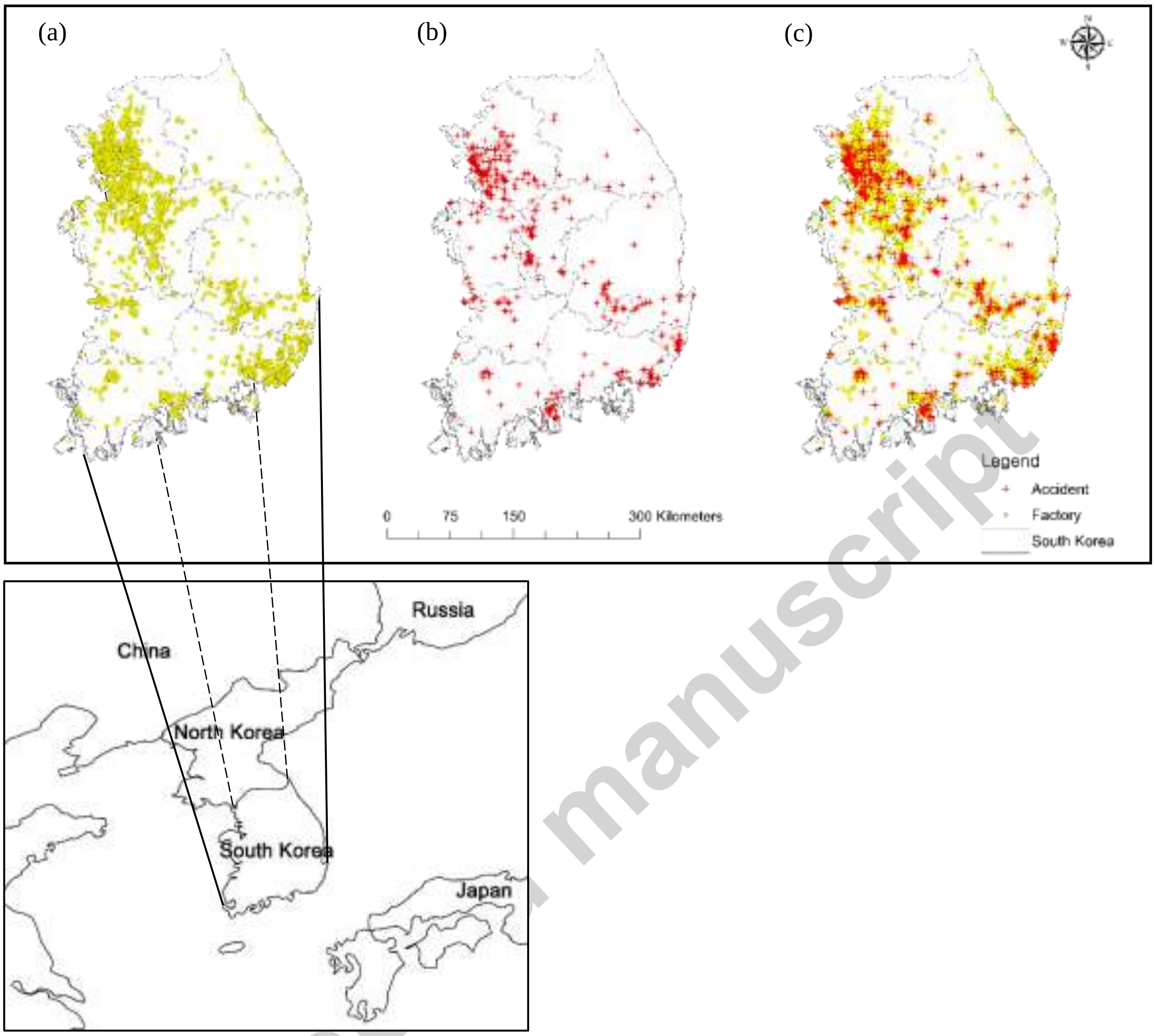
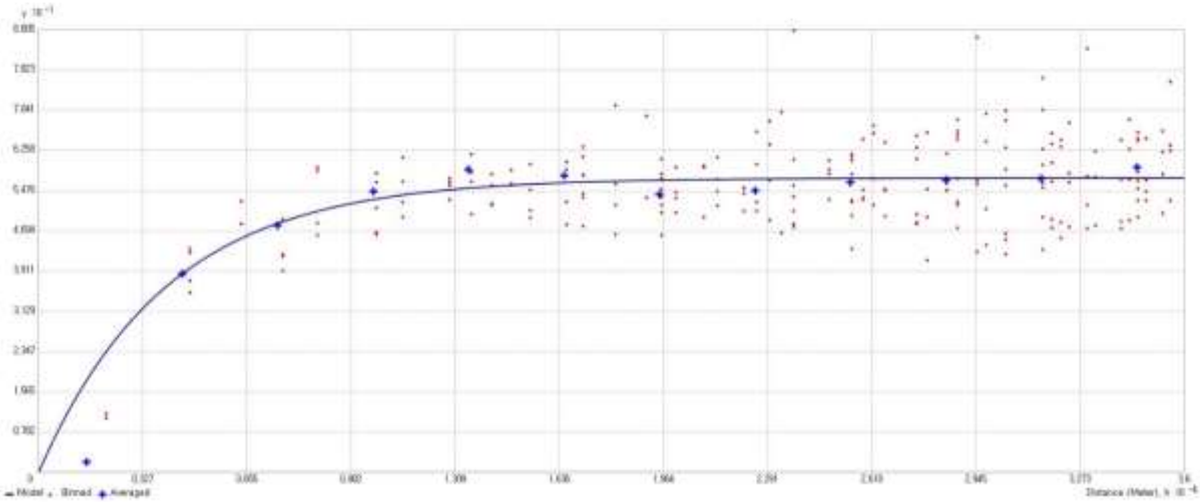
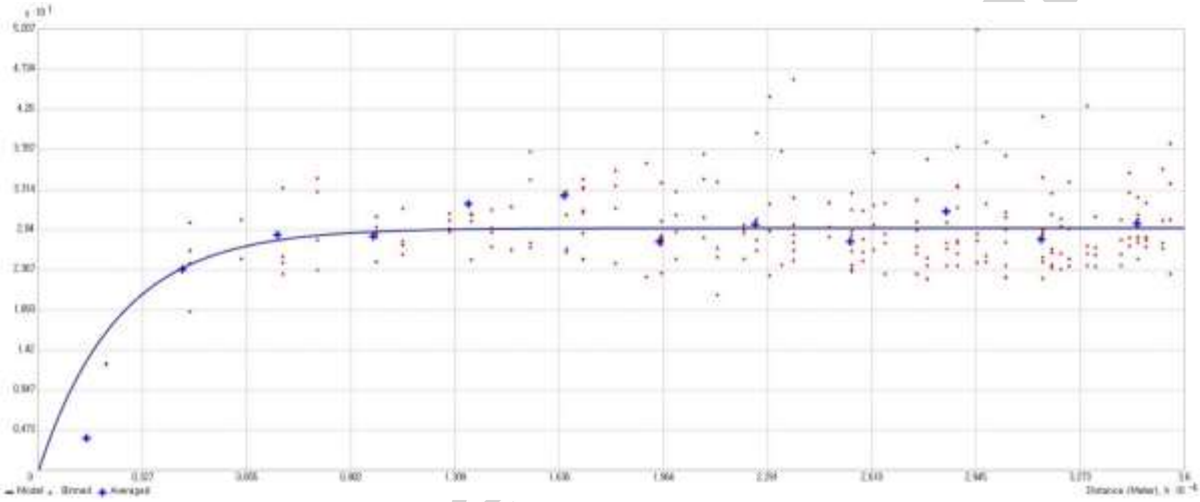


Figure 1. Spatial distribution of chemical factories and accidents in South Korea

(a. Chemical factory, b. Chemical accident, c. both)

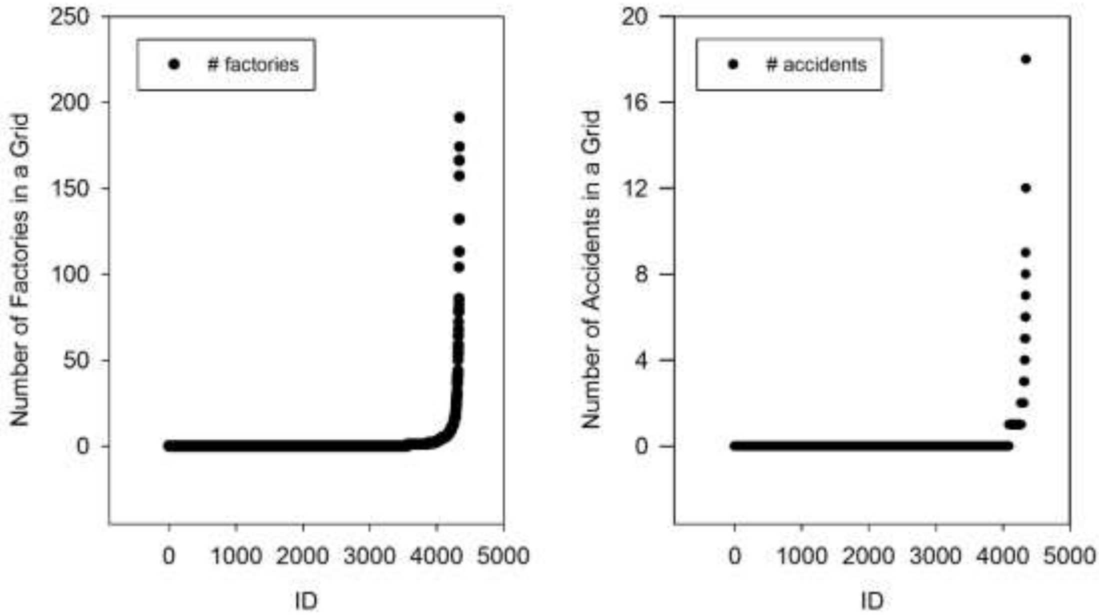


(a) Chemical factory



(b) Chemical accident

Figure 2. Result of Spatial autocorrelation



(a) Number of factories in a grid (b) Number of accidents in a grid

Figure 3. Geometrical series variables

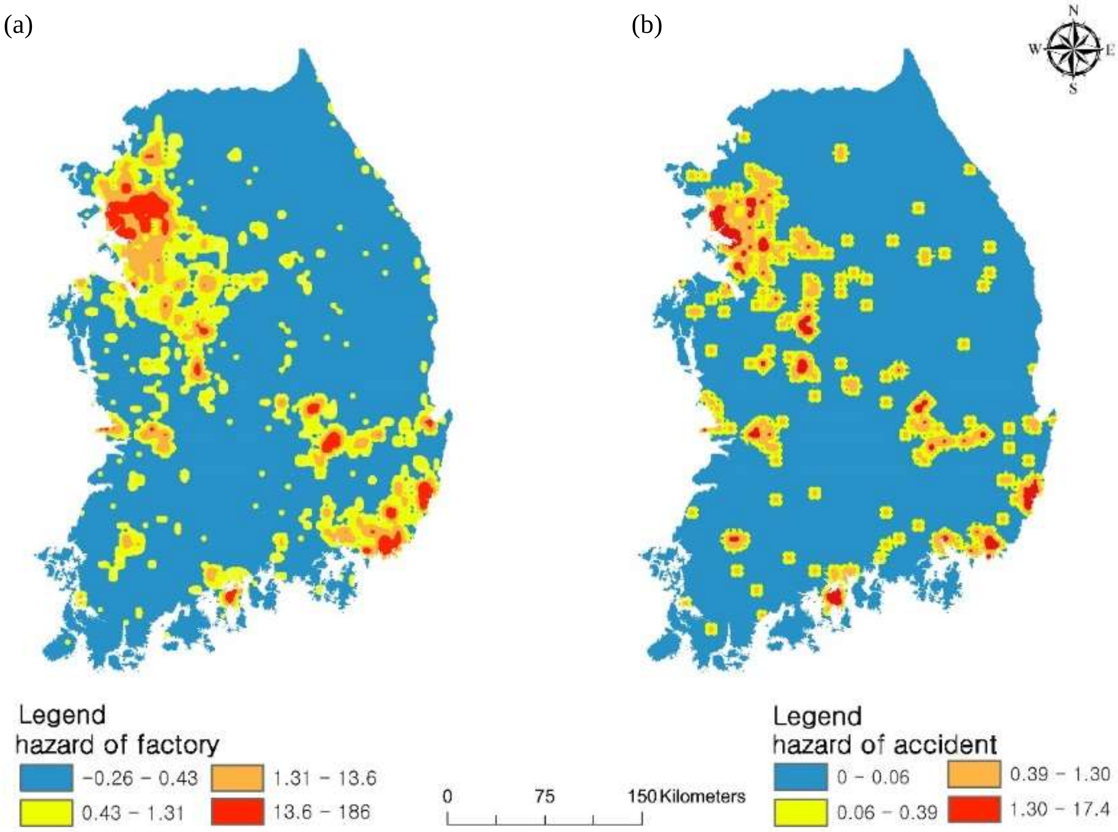


Figure 4. Hazard map from (a) chemical factories and (b) chemical accidents

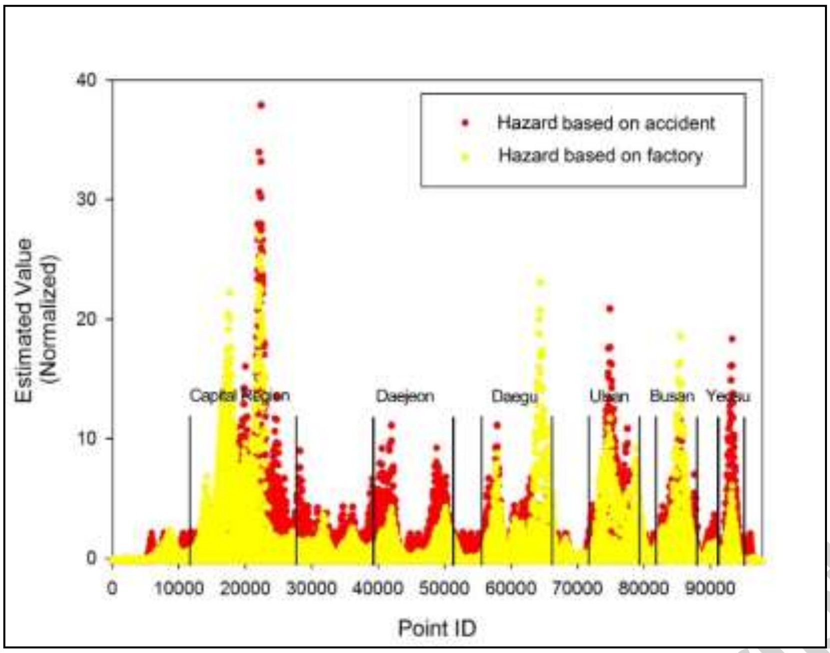


Figure 5. Spatial similarity of estimated hazard of chemical accidents and factories

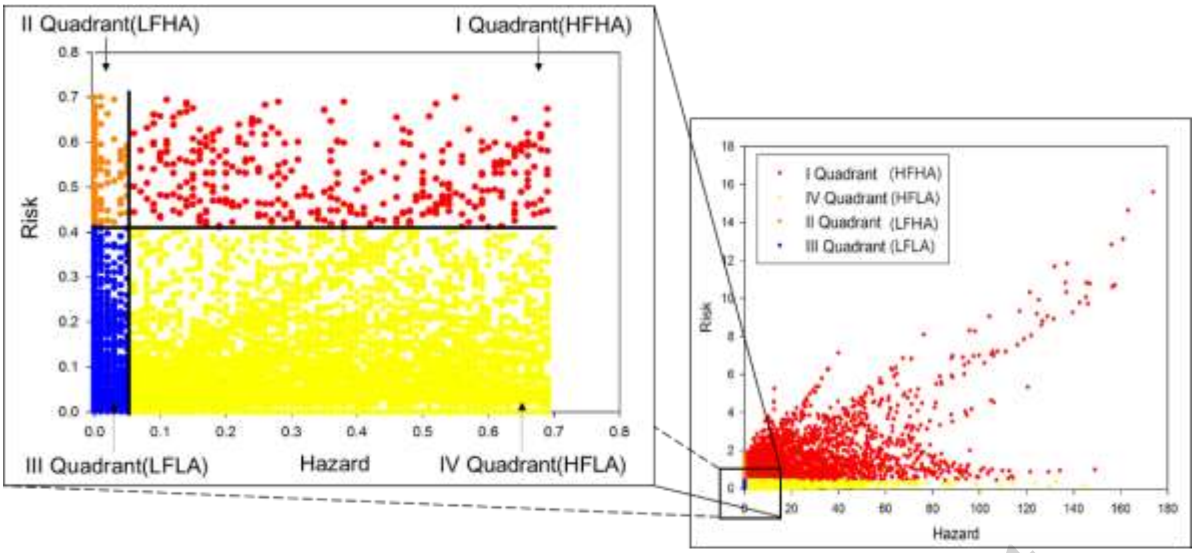


Figure 6. Geometric interval applied on estimated hazard of factories and accidents

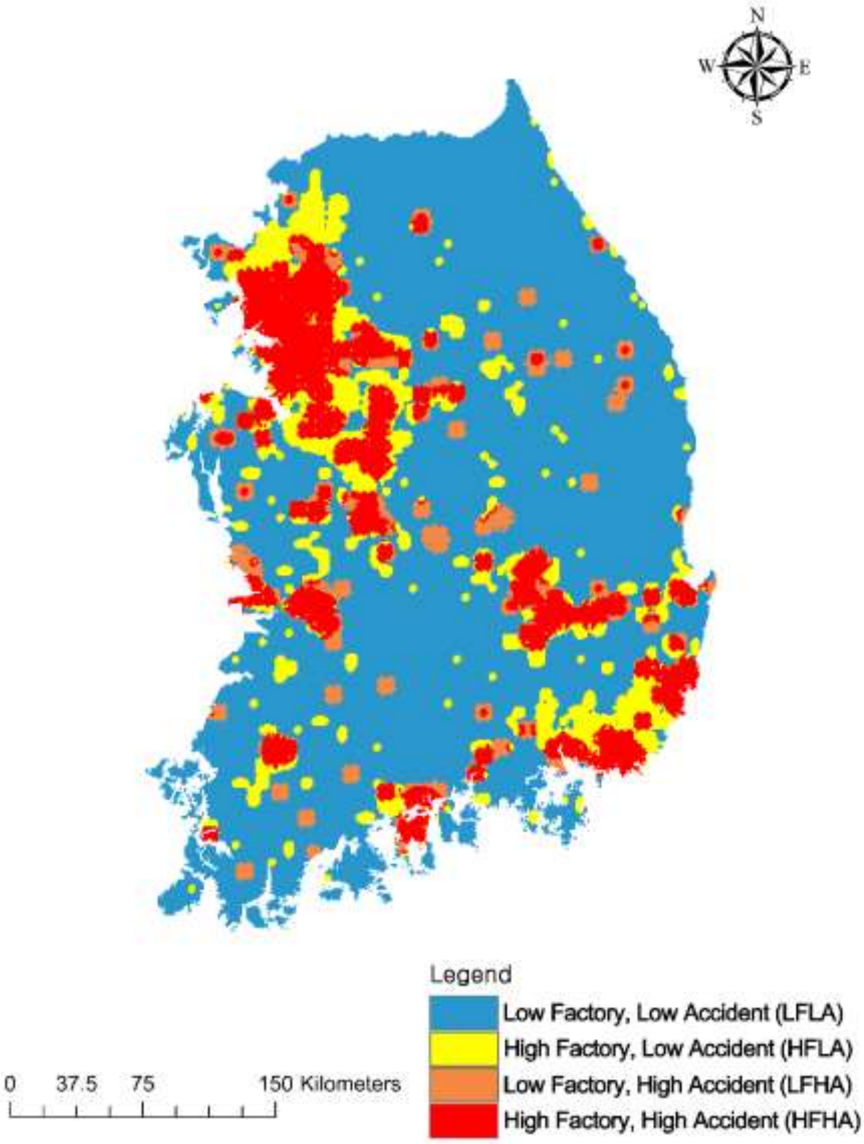


Figure 7. Chemical Accident Hazard Assessment Map

Table 1. Verification of hazard estimation

Type	Year	Hazard Level	Capital region	Busan city	Daegu city	Daejeon city	Ulsan city	Yeosu city	South Korea
Number of accidents in estimated hazard map from chemical factories	2013 ~2015	High	84 (86.0%)	14 (94.1%)	5 (76.0%)	11 (85.1%)	26 (97.7%)	15 (90%)	164 (83.7%)
		Medium	63 (13.8%)	6 (5.9%)	5 (24.0%)	1 (14.9%)	5 (2.2%)	2 (4.1%)	183 (15.4%)
		Low	10 (0.2%)	0 (0%)	0 (0%)	0 (0%)	1 (0.1%)	3 (5.9%)	73 (0.9%)
	2016 ~2017	High	13 (89.5%)	4 (96.5%)	2 (76.5%)	4 (100%)	5 (100%)	3 (74.7%)	34 (87.8%)
		Medium	7 (10.3%)	1 (3.5%)	0 (0%)	0 (0%)	0 (0%)	3 (25.3%)	26 (11.0%)
		Low	2 (0.3%)	0 (0%)	1 (23.5%)	0 (0%)	0 (0%)	0 (0%)	18 (1.1%)
	2003 ~2017	High	97 (86.5%)	18 (94.6%)	7 (76.1%)	15 (91.1%)	31 (98.1%)	18 (87.0%)	198 (84.4%)
		Medium	70 (13.3%)	7 (5.4%)	5 (17.2%)	1 (8.9%)	5 (1.9%)	5 (1.9%)	209 (14.6%)
		Low	12 (0.2%)	0 (0%)	1 (6.7%)	0 (0%)	1 (0.1%)	3 (0.1%)	91 (0.9%)
Number of accidents in estimated hazard map from chemical accidents	2016 ~2017	High	13 (89.5%)	3 (89.0%)	2 (76.5%)	3 (96.0%)	5 (100%)	3 (89.8%)	28 (84.5%)
		Medium	7 (10.3%)	1 (4.4%)	0 (0%)	1 (4.0%)	0 (0%)	1 (10.2%)	28 (13.9%)
		Low	2 (0.3%)	1 (6.6%)	1 (23.5%)	0 (0%)	0 (0%)	0 (0%)	22 (1.6%)

Table 2. Verification of the four-classification result by HFHA (High Factory and High Accident), LFHA (Low Factory and High Accident), HFLA (High Factory and Low Accident), LFLA (Low Factory and Low Accident).

Number of accidents in four classes								
		Capital region	Busan city	Daegu city	Daejeon city	Ulsan city	Yeosu city	South Korea
2013 ~2015	HF, HA	157 (86.3%)	18 (100%)	10 (100%)	12 (100%)	31 (100%)	19 (66.0%)	379 (77.5%)
	LF, HA	3 (13.7%)	0 (0%)	0 (%)	0 (0%)	0 (0%)	2 (34.0%)	39 (22.5%)
	HF, LA	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	LF, LA	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
2016 ~2017	HF, HA	19 (63.3%)	4 (74.5%)	2 (45.1%)	4 (100%)	5 (100%)	4 (100%)	58 (75.9%)
	LF, HA	1 (27.8%)	1 (25.5%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	2 (7.3%)
	HF, LA	1 (5.7%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	9 (14.5%)
	LF, LA	1 (3.3%)	0 (0%)	1 (54.9%)	0 (0%)	0 (0%)	0 (0%)	9 (2.3%)
2013 ~2017	HF, HA	176 (83.0%)	22 (94.1%)	12 (83.2%)	16 (100%)	36 (100%)	23 (70.2%)	437 (77.3%)
	LF, HA	4 (15.7%)	1 (5.9%)	0 (0%)	0 (0%)	0 (0%)	2 (29.8%)	41 (20.5%)
	HF, LA	1 (0.8%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	9 (2.0%)
	LF, LA	1 (0.5%)	0 (0%)	1 (16.8%)	0 (0%)	0 (0%)	0 (0%)	9 (0.3%)

Number of factories in four classes

		Capital region	Busan city	Daegu city	Daejeon city	Ulsan city	Yeosu city	South Korea
2016 ~2017	HF, HA	2589 (83.1%)	381 (79.8%)	349 (90.8%)	87 (83.3%)	333 (83.9%)	106 (81.9%)	4916 (82.2%)
	LF, HA	2 (0.5%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (3.8%)	6 (0.3%)
	HF, LA	299 (16.4%)	60 (20.2%)	11 (9.2%)	4 (16.7%)	16 (16.1%)	2 (14.3%)	856 (17.6%)
	LF, LA	2 (0.1%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	23 (0.1%)