Gold in the Central Lapland Greenstone Belt, Finland
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PROSPECTIVITY ANALYSIS OF GOLD USING REGIONAL GEOPHYSICAL AND GEOCHEMICAL DATA FROM THE CENTRAL LAPLAND GREENSTONE BELT, FINLAND

by
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Two spatial modeling techniques, empirical weights of evidence and conceptual fuzzy logic, were used to predict the most prospective areas for gold exploration within the Paleoproterozoic Central Lapland Greenstone Belt in Northern Finland. The study area covers almost 20 000 km^2 in a terrain with excellent infrastructure and easy access in spite of situating in a region some 100 km north from the Arctic Circle.

For the empirical model the spatial association between the known mineral occurrences and selected evidential geoscientific datasets were quantified and used to generalize the original datasets into binary predictor patterns indicating favorable areas. The conceptual model, on the other hand, was created by using expert opinions on the significance of the anomalies within the evidential datasets.

The data used were high-resolution airborne geophysics, regional gravity, and regional scale multi-element till geochemistry. Both methods, empirical and conceptual, give comparable results, which were geologically validated and verified to be meaningful. The models used predicted well the known deposits and highlighted also areas with past and future exploration interest. Both empirical and conceptual approaches proved to be suitable for the purpose and the regional geochemical, geophysical and geological data appeared to be appropriate for regional or reconnaissance scale first stage exploration. According to the evidential data used and the models produced, the Central Lapland Greenstone Belt has regions with high potential for new greenstone hosted orogenic type of gold occurrences to be found.

Key words (Georef Thesaurus, AGI): mineral exploration, gold ores, Central Lapland Greenstone Belt, geophysical methods, geochemical methods, weights of evidence, fuzzy logic, models, geographic information systems, Paleoproterozoic, Kittilä, Sodankylä, Lapland Province, Finland.

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INTRODUCTION

The geological information collected from the Central Lapland Greenstone Belt (CLGB) is composed of multiple layers of spatial data at several scales and with variable coverage over the area of interest. The total study area used in this project is 18 790 km^2 (Fig. 1), covering the essential parts of the CLGB.

The data available includes airborne high-resolution multi-element geophysical surveys, regional and local scale geochemical surveys and geological mapping in variable scales. There is a need for tools to efficiently and properly manage, manipulate, visualize and integrate this large amount of data. Having the data in digital format gives one an excellent opportunity to utilize Geographic Information Systems (GIS) to be used for quantitative analysis of spatial association between the known mineral occurrences and the variable geological features. The aim of this paper was to make a prospectivity analysis for gold within the CLGB and also to illustrate the possibilities to conduct this task by using the geo-scientific data sets from Northern Finland and certain selected methods as examples of spatial modeling tools. Furthermore, the goal was to use the data sets to make estimations on the most prospective areas for gold by using these spatial analytical techniques. The strengths of the GIS tools used is this ability to integrate and combine multiple geoscientific information into a single prospectivity map, i.e. to condense and generalize from a complex

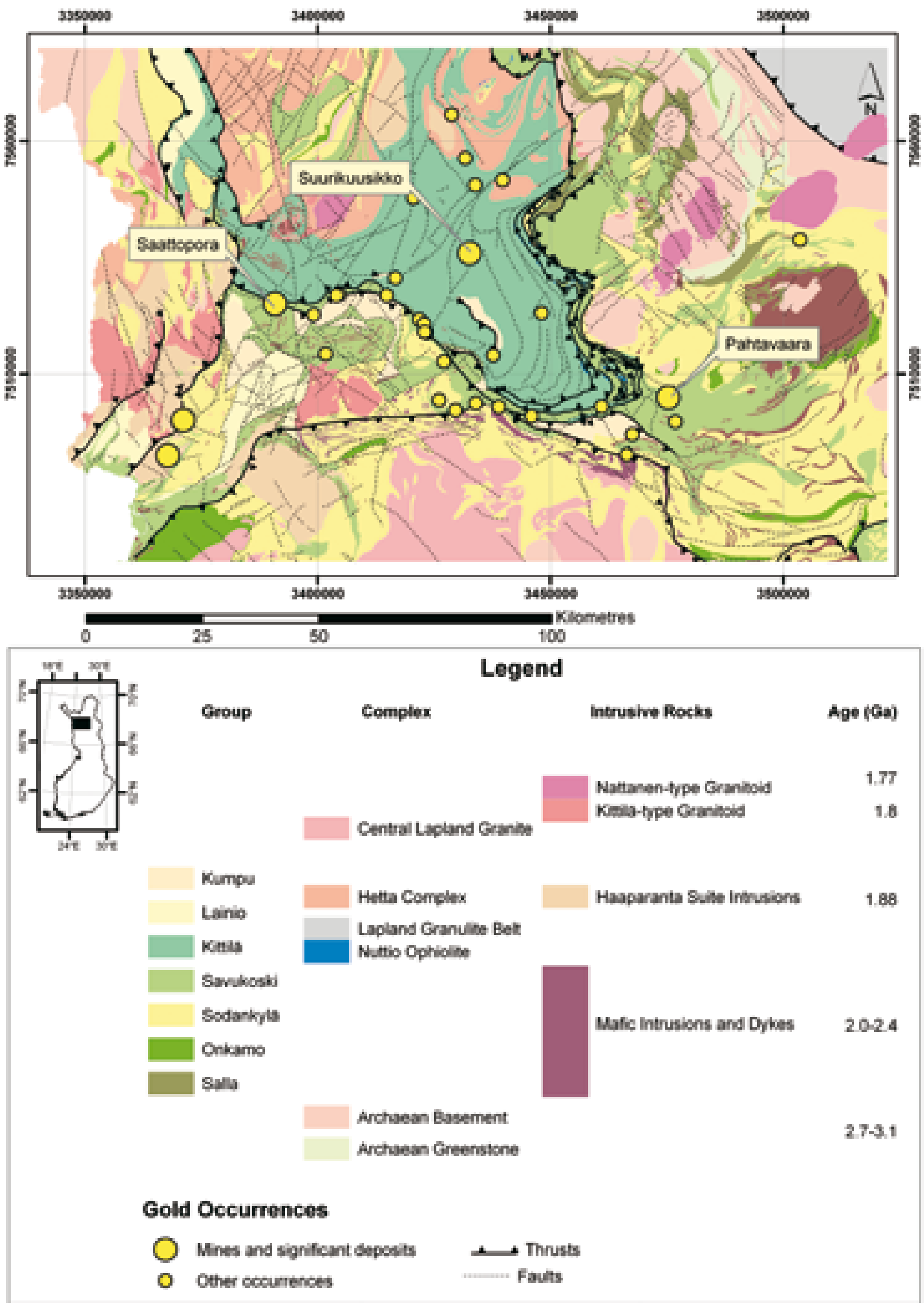

Fig. 1. Location of the study area in Lapland. The known gold occurrences and deposits marked with yellow dots. The most significant deposits are labeled.

Table 1. Empirical and conceptual methods for mineral prospectivity mapping (Bonham-Carter, 1994, Harris et al. 2001).

Type	Method	Model parameters	Criteria from combining input data
Empirical *(data driven)*	Weights of evidence	Calculated from training data (i.e. existing mineral deposits)	Spatial relationship between the known occurrences and input data (use of Bayesian probabilities)
	Logistic regression Neural networks	Calculated from training data (i.e. existing mineral deposits)	Use of training areas around each deposit to gather statistics from each of the input layers; Used to predict the presence or absence of a mineral deposit
Conceptual *(knowledge driven)*	Boolean logic	Estimated by an expert	Summing of binary maps
	Index overlay	Estimated by an expert	Summing of weighted binary maps
	Dempster-Shafer belief theory	Estimated by an expert	A generalization of the Bayesian theory of subjective probability.
	Fuzzy logic	Estimated by an expert	Each input predictor map assigned a fuzzy weight ranging from 0 to 1; all predictor maps then combined using fuzzy operators

mass of information into a substantially simpler form suitable for exploration or land use decisions.

Several tools for statistical and geo-statistical operations may be used to conduct mineral prospectivity mapping. These methods can be divided into two main categories (Table 1), based on the approach: (I) empirical (data driven) and (II) conceptual (knowledge driven) methods (Bonham-Carter, 1994). In the empirical approach, the known mineral deposits are used as 'training points' for examining spatial relationships between the known deposits and particular geological, geochemical and geophysical features. The identified relationships between the input data and the training points are quantified and used to establish the importance of each evidence map and finally integrated into a single mineral prospectivity map. Examples of the empirical methods used are weights of evidence, logistic regression and neural networks. The other major branch is the conceptual (knowledge driven) approach, where we use re-formulation of knowledge about deposit formation into mappable criteria (i.e. threshold values in geochemistry and geophysics etc., certain structures or formations in the geological maps). The areas that fulfill the majority of these criteria are highlighted as being the most prospective. These methods are dependent on the geologist's input and exploration models being thus fairly subjective in nature. By selecting a conceptual method one can benefit from the expertise of the geologists during the modeling process exceeding the capabilities of pure statistics. The methods belonging into this branch include Boolean logic, index overlay (binary or multi-class maps), the Dempster-Shafer belief theory, and fuzzy logic overlay. Especially the latter has been recently widely implemented for the data integration and mineral prospectivity mapping purposes (Chung and Moon, 1990; An et al., 1991, D'Ercole et al., 2000; Knox-Robinson, 2000, Luo and Dimitrakopoulos, 2003).

Direct comparison between these two different approaches (empirical vs. conceptual) is difficult since the methods do not use identical datasets (Singer and Kouda, 1999; Harris et al., 2001). The selection of the preferable method is thus often made based on the available datasets and the goals of the modeling. Harris et al. (2001) give an excellent summary of the different methods. Different methods bring their own characteristics into modelling and allow one also to use them to cross-validate results from one method to another.

METHODS

For this study the multivariate empirical method called weights of evidence (Bonham-Carter et al., 1988; Agterberg et al., 1990) and a conceptual fuzzy logic overlay method were selected for the data integration and analysis. The weights-of-evidence method is based on a log-linear form of Bayes' rule including an assumption that the evidential explanatory categorical (geological maps etc.) or ordered (geochemical and geophysical) variables are conditionally independent with respect to the deposits and occurrences used as training points. The GIS software used in this study is ArcView^{TM} with Spatial Analyst^{TM} (ESRI products).

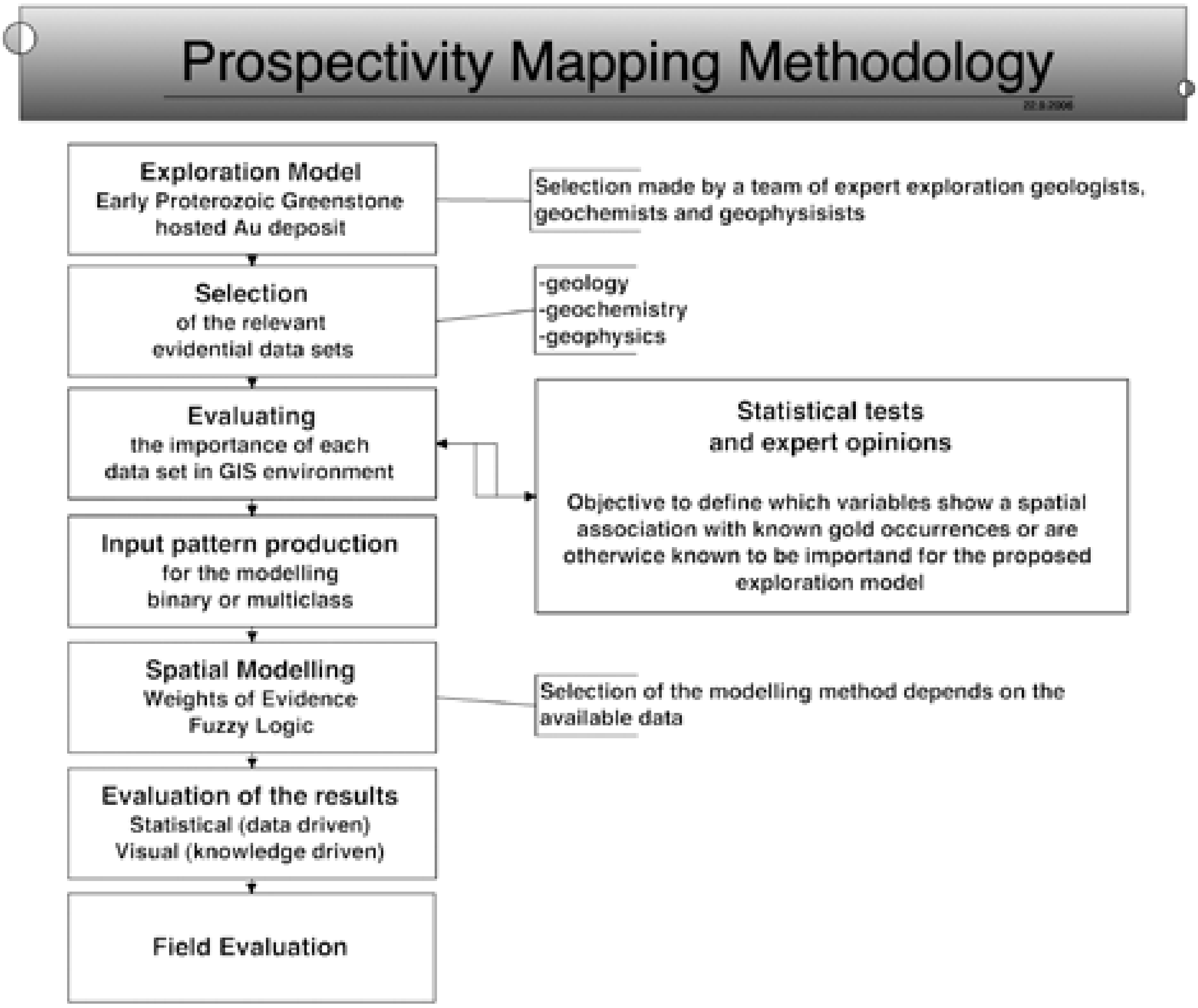

Fig. 2. Flow chart of the methodology used to produce prospectivity maps.

The weights-of-evidence and fuzzy-logic modeling were carried out by using an ArcView add-on called ArcSDM, which is a tool developed by the Geological Survey of Canada and the U.S. Geological Survey (Kemp et al., 2001).

Figure 2 shows how prospectivity mapping methodology can be divided into independent modules. The key issue is the exploration model, which is based on the expertise of the exploration team of geologists, geochemists and geophysicists.

Weights-of-evidence method

The weights-of-evidence method is based on the application of Bayes' Rule of Probability with an assumption of conditional independence (Bonham-Carter, 1994). When this assumption is violated, one can run logistic regression to calculate the posterior probabilities. The essence of the Bayesian approach is to provide a mathematical rule explaining how you should change your existing beliefs in the light of new evidence. In other words, it allows scientists to combine new data with their existing knowledge or expertise. In the weights of evidence modelling this is expressed in terms of prior and posterior probabilities, which are derived in the context of mineral exploration by calculating the spatial association of the known mineral occurrences or deposits (training sites) and the selected series of evidential maps. If the number of training sites falls mostly within a predictor pattern, it is evident that the probability of a training site occurring inside the pattern is higher than the prior probability. Respectively, the probability of having a training site outside the pattern is lower than the prior probability.

Table 2. Terminology used in weights of evidence modeling.

Term	Description
Training site or point	The known locations of which is being predicted. In this study the training sites are known Au deposits and occurrences within the study area
Study area/ analysis extend	The area to be studied and used as the analysis mask.
Evidential theme/ evidence	Maps used for prediction of point objects (mineral occurrences). These can be either in vector or raster format and either binary or multi-class.
Unit cell area/ response theme	The area, which the training sites are assumed to occupy. This is used in order to calculate the probability of the point occurrences. The output of the modeling is a map (response theme) showing the probability that a unit area contains a point i.e. an Au deposit in this study.
Pattern	A map area having consistent, recognizable characteristics.
Weight, W^+, W^-	The value assigned to a pattern as a predictor of the training sites. The weight for inside pattern is denoted as W+ and outside pattern is W-. The weights for areas of missing data are given a value of zero.
Contrast, C	Difference between W+ and W- indicating how well a pattern predicts the training sites. A positive contrast that is significant based on its studentized contrast suggests that a pattern is a useful predictor. The relative values of contrast of the various patterns used in a model indicate the relative degree of importance of each patterns as a predictor.
Confidence (studentized contrast, Stud(C))	The ratio of the contrast and the standard deviation of the contrast. This is used in similar manner to a Student t-test of significance of the contrast. A useful measure of significance of the contrast due to the uncertainties of the weights and missing data.
Prior probability	The probability of a training site occurring per study area (the density of training sites in the study area) before consideration of the evidence.
Posterior probability	The prior probability modified by consideration of the evidence from one or more patterns. The posterior probability is calculated by adding a weight for each pattern to the logit of the prior probability and converting the sums from logits to probability. These calculations assume that the patterns added are conditionally independent.

Bonham-Carter (1994), Raines (1999), Singer and Kouda (1999), Carranza and Hale (2000) provide the detailed formulation of the weights of evidence model, which is only briefly described here. The main terminology used in the spatial modelling is described in the Table 2 (chiefly after Bonham-Carter, 1994; Raines, 1999).

By quantifying the degree of overlap between the training sites and the patterns of the evidential data one can calculate a pair of weights (W^+ and W^-) for each piece of evidence. If more points occur within a pattern than would be due to chance then W^+ is positive and W^- is negative. On the other hand, when W^+ is negative and W^- is positive then there are fewer points within the pattern that would be expected by chance. A positive W^+ value indicates thus a positive association between the training points and the evidence map, whereas a positive W^- value indicates a negative association respectively. By calculating the difference or contrast ($C = W^+ – W^-$) between these two weights for each of the evidential maps, one can get a measure of the association between training sites and these evidence maps (Bonham-Carter et al., 1988). A stronger association shows as higher contrast value. The studentized value of the contrast, the ratio of contrast to its standard deviation, C/s(C), is calculated to test the significance of the contrast values (referred to in ArcSDM as the 'confidence' value). The confidence value gives an estimate of the uncertainty included in the weights calculation. The contrast values are used to generalize the evidential themes from multi-class maps into binary pattern maps indicating areas within each of the maps to be either "favourable" or "non-favourable". The maximum contrast value can be used to point out the threshold to identify an anomaly in the data. The generalization of the multi-class themes is beneficial since the small number of the rare mineral deposits can lead to noisy and unreliable estimates of weights.

By using the presence of a predictor pattern we can then calculate the posterior probability, which is the prior probability multiplied by a factor which depends on the frequency with which training points occur on an evidential map. Posterior probability is larger than prior probability in the areas where the sum of the weights is positive.

Fuzzy Logic method

The conceptual approach is using the expertise of the exploration geologists, geochemists, and geophysicists to define the threshold values for the evidential datasets. For this study, the fuzzy-logic spatial modeling was also produced by using ArcSDM software (Kemp et al., 2001). In classical set theory, the membership of a set is defined as true or false (1 or 0) whereas membership of a fuzzy set is expressed on a continuous scale from 1 to 0 (e.g. somewhere between 'anomalous' vs. 'not anomalous') as shown in Figure 3. The values of fuzzy membership can be chosen based on subjective judgment of an expert. In this study, the fuzzy membership function for each evidential element was defined by experts by taking in account the statistics of each element and the geological background values within each area of interest. Membership reflects degree of truth of some proposition or hypothesis, which is often a linguistic statement such as high magnetic values are anomalous for gold deposits. To define the membership function one needs to define the thresholds for 'not anomalous' and 'anomalous' values and then a function describing the 'maybe – probably' values in between these two thresholds. In this work, a linear function between the thresholds was assumed appropriate, but the shape of the actual function varies due to classification prior giving fuzzy membership values for the classes of the maps (Fig. 3). The fuzzy membership values reflect the relative importance of the each class of the maps used. The closer the fuzzy membership value is to one the more significant is the anomaly. The hypothesis derived from the exploration model was 'is there a gold deposit' and the fuzzy sub sets or intermediate hypotheses were like 'data showing an alteration zone' and 'data showing signs of sulphides'.

After defining the fuzzy membership functions for each evidential map, a variety of operators can be used to combine the membership values together. In this paper, we have used the operators listed in Table 3 (chiefly after Bonham-Carter, 1994).

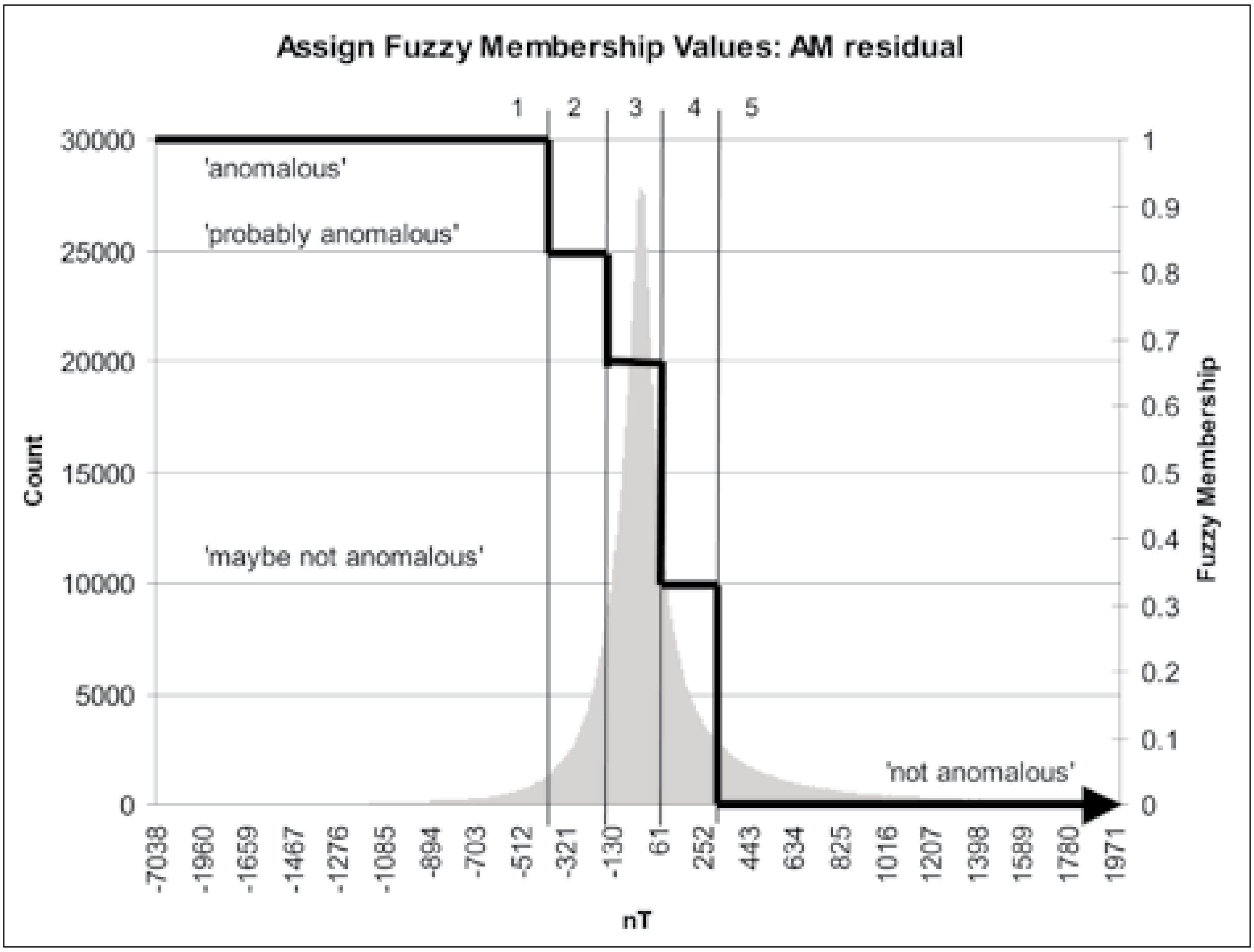

Fig. 3. An example of assigning fuzzy membership values (thick black line). Fuzzy membership value of 1 is 'anomalous' and 0 is 'non-anomalous'. Values between 1 and 0 represent statements 'probably anomalous', 'maybe not anomalous' etc. The original data values were broken into a small number of meaningful classes by using the histogram and then the experts assigned fuzzy-membership values to the classes.

Table 3. Fuzzy operators (Bonham-Carter, 1994).

Operator	Boolean equivalent	Desrciption
Fuzzy AND	AND (logical intersection)	This could also be called as Min-operator as it creates an output, which is controlled by the smallest fuzzy membership values at each location. It results in a conservative estimate of set membership, with tendency to produce small values and minimum areas. Useful to find the areas where all the evidence used need to be present for the hypothesis to be true.
Fuzzy OR	OR (logical union)	This could be called as Max-operator as it creates an output, whose membership values are controlled by the maximum values of any of the input maps. By using this operator any positive evidence may be sufficient to suggest favourability.
Fuzzy Algebraic Product		The combined fuzzy membership values tend to be very small due to the effect of multiplying several numbers less than 1. The output is always smaller than, or equal to, the smallest contributing membership value.
Fuzzy Algebraic Sum		The result is always larger (or equal to) the largest contributing membership value.
Fuzzy Gamma		This is defined in terms of the fuzzy algebraic product and the fuzzy algebraic sum, being a combination of these two operations.

DESCRIPTION OF THE DATASETS

The data used for this study are multi-element low-altitude airborne geophysics, regional gravity, and multi-element till geochemistry. All the basic data are standard data sets produced by the GTK and available on request. The locations of the known Au deposits were taken and slightly modified from the FinGOLD database (Eilu, 1999). For certain larger deposits a few more points were added and some locations were relocated more precisely. The total amount of available training points is 40 representing the Early Proterozoic greenstone hosted gold deposits and occurrences within the study area. For the modeling, we used 35 training points excluding those that were closely clustered together.

High resolution airborne geophysics

The whole study area has been covered by high resolution, systematic, low altitude airborne geophysics. The oldest flights date from 1974 and the most recent were completed during the summer 2002. The mapped properties are magnetic total field intensity, two electromagnetic field components and four gamma radiation components. In this work, aeromagnetic and apparent resistivity of conductive half space calculated from airborne electromagnetic measurements has been used. The flight altitude used is about 30 to 40 meters and line spacing 200 meters. The profile direction has been either N-S or E-W according to the dominant strike of the bedrock. As the flying speed is around 50 m/s, and the recordings has been done two to ten times per second in magnetic and two or four times per second in electromagnetic measurements, the data point separation depending on method is five to 25 meters. The cell size of interpolated grids is 50 m x 50 m.

Known gold occurrences and deposits of CLGB have a strong lithological and structural control, and host rocks are affected by strong multi-stage alteration (Airo and Mertanen, 2001). Large crustal-scale structures, faults, shear, and in many places alteration zones produce observable aeromagnetic lows. To enhance these magnetic lows a median filter was applied by subtracting from the original aeromagnetic data the median value of a four km circular radius neighborhood around each of the cells within the grid. The residual of the aeromagnetic grid was then used in the modeling instead of the original grid. In CLGB, most known gold occurrences are associated with sulphide alteration and sulphides can produce conductivity anomalies. However, conductive graphite bearing volcanic-metasedimentary rocks make the situation more complex. Filtering the resistivity data did not improve the results. Thus, the original resistivity grid was used in the model. Although alteration zones can in some cases be mapped using radiation data, the use of gamma radiation is hampered as, radiation attenuates to zero within the first 30 cm from the source. In this study, the aeroradiometric data has not been used due to large differences in soil cover, large bog areas, lakes and rivers, which unevenly mask the radiation. Aerogeophysical applications for gold exploration in CLGB has been reviewed by Airo (2006).

Regional gravity

Gravity reflects large crustal-scale structures, lithological units, faults, and shear zones, which can be associated with gold occurrences. Bouguer anomaly data were interpolated to grid cell size of 500 m x 500 m and the horizontal gradient was calculated for the analysis.

The CLGB regional gravimetric survey has been done with a point density of one point/km^2 on the average by GTK and partly also by the Finnish Geodetic Institute (Kääriäinen and Mäkinen, 1997). Regional gravity data measured in CLGB have been described by Salmirinne and Turunen (2007). The gravity survey covers about 62% of the whole study area. In the weights-of-evidence method, training sites in areas of no data were not used for calculation of weights for the gravity theme and these no data areas are treated as “missing data” for which the weights are set to zero. In the fuzzy-logic method these areas of missing data are assigned area-weighted mean of the fuzzy membership of known data. So, in spite of low data density and “missing data” areas, it has been possible to use gravity data, which proved to be meaningful for the analysis.

Regional till geochemistry

The sampling density for the regional till geochemistry is one sample per four km^2. The sampling was conducted in the 1980’s (Salminen, 1995). In general, the samples were collected as a composite of three to five sub-samples from an average depth of 1.5 meters taken with a portable percussion drill equipped with a through flow bit. In certain areas, the samples were combined from five to ten line samples, which has caused some artifacts shown as level differences between the map sheets with single samples. The sampled material was chemically unaltered parent till. The samples were dried and the <0.06 mm fraction was sieved for analysis. Hot aqua regia digest was used and Al, Ba, Ca, Co, Cr, Cu, Fe, K, La, Li, Mg, Mn, Mo, Ni, P, Pb, Sc, Sr, Th, Ti, V, Y, Zn and Zr were determined with ICP-AES. In addition, Au, Te and Pd were analyzed with AAS. The original point data were interpolated to grid cell size of 200 m x 200 m.

Geology

Geological mapping has been conducted over the study area mostly at 1:50 000 scale, which are compiled into 1:100 000 scale printed maps and a generalized 1:200 000 scale digitized stratigraphical map of the Kittilä Greenstone Area (Lehtonen et al., 1998). The geological outline of CLGB is given by Hölttä et al. (2007).

Outcrop conditions are generally poor and these areas have been subject only to the first stage exploration, which has typically involved only till sampling and airborne geophysics in addition to geological mapping.

The geological map is based on field mapping guided by interpretation of the airborne geophysics. Thus, there is quite clear correlation between for example the magnetic data and the geological map. In this study, we have avoided the use of the interpreted geological map together with the airborne geophysics. The scale of the geological map currently available also limits its use for spatial modeling together with the high-resolution airborne geophysics. The 1:100 000 geological maps would provide more details and variability to lithological units compared to generalized 1:200 000. We expect to be able to improve the models when the larger scale geological maps of the entire study area are available.

WEIGHTS-OF-EVIDENCE MODELING

To accomplish weights-of-evidence modeling, the original multi-class evidential datasets were generalized into binary predictor patterns. The evidence used were: (1) selected pathfinder elements in till geochemistry and (2) favorable geophysical anomalies. The geological map was not used as evidence, even though it might provide relevant information. The final results of the modeling are, however, compared with and validated by using the geological map.

After calculating the weights for each evidential data, one can use the variation of the weights and the calculated contrasts (i.e. difference between the weights) to select the classes where the spatial association between the training sites and the evidential data sets is optimal i.e. at the maximum contrast value. The evidential data is then divided into two classes (e.g. ‘favorable’ and ‘non-favorable’), which will be used as an input in the data integration.

Figure 4 shows the results of the generalization of the geophysical and combined geochemical data sets. Table 4 is an example of the weights analysis used for generalization. These binary prediction patterns

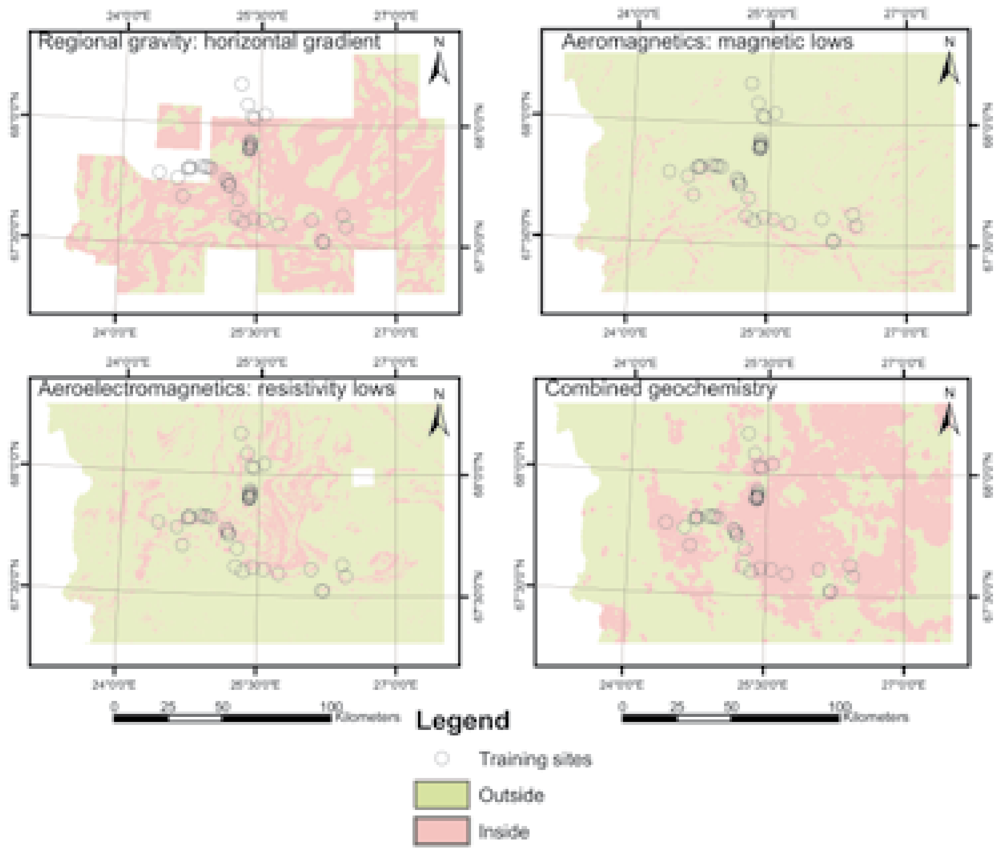

Fig. 4. Binary patterns derived from the generalization of the geophysical and combined geochemical evidential data sets. Green areas are classified as ‘‘non-favorable pattern and red areas as ‘favorable’ pattern. The open circles are the known Au –occurrences and deposits used as training sites. Combination of geochemistry is done by fuzzy logic overlay in three steps. First Fe, As, Te and Ni fuzzy membership values are combined together by using Fuzzy OR operator resulting a combination, which is integrated together with Cu fuzzy membership values by using a Fuzzy AND operator. Finally Au fuzzy membership values are combined with this combination by using a Fuzzy Gamma operator.

Table 4. Weights for airborne magnetics as an example of the weights analyses used for generalizing the magnetic evidence. Class 1 (bold font) was considered as favorable predictor pattern (maximum contrast) and the rest as non-favourable, respectively. The s(W^+), the s(W^-) and the s(C) stand for the standard deviations of the corresponding factors. Stud(C) is the studentized contrast value of C/s(C). #Points = cumulative number of training sites.

Class	Class range (nT)	Area (Sq. km)	#Points	W+	s(W+)	W-	s(W-)	Contrast	S(C)	Stud(C)
1	–7040 – –270	1303.3	9	1.3113	0.3339	–0.2254	0.1962	1.5368	0.3873	**3.9681**
2	–270 – –170	2571.6	12	0.9183	0.2890	–0.2727	0.2086	1.1909	0.3564	3.3413
3	–170 – –110	4053.4	12	0.4624	0.2889	–0.1766	0.2086	0.6390	0.3563	1.7933
4	–110 – –80	5143.0	13	0.3041	0.2775	–0.1441	0.2133	0.4482	0.3500	1.2805
5	–80 – –50	6589.1	14	0.1303	0.2674	–0.0783	0.2183	0.2085	0.3452	0.6041
6	–50 – –30	7802.3	15	0.0302	0.2583	–0.0220	0.2237	0.0522	0.3417	0.1527
7	–30 – –10	9174.3	17	–0.0067	0.2426	0.0064	0.2358	–0.0131	0.3384	–0.0387
8	–10 – 10	10402.3	19	–0.0211	0.2295	0.0257	0.2501	–0.0468	0.3395	–0.1378
9	10 – 30	11463.6	23	0.0729	0.2086	–0.1264	0.2888	0.1993	0.3563	0.5593
10	30 – 60	12647.4	25	0.0580	0.2001	–0.1317	0.3164	0.1897	0.3743	0.5068
11	70 – 110	13954.3	29	0.1081	0.1858	–0.4023	0.4084	0.5104	0.4487	1.1377
12	110 – 190	15219.5	31	0.0880	0.1797	–0.5024	0.5001	0.5904	0.5314	1.1110
13	190 – 320	16363.7	31	0.0154	0.1797	–0.1121	0.5002	0.1276	0.5315	0.2400
14	320 – 630	17572.2	31	–0.0559	0.1797	0.5897	0.5004	–0.6456	0.5317	–1.2141
15	630 – 13820	18762.1	35							

were then pair wise tested for conditional independence to assure that the following modeling would not give over or underestimated results due to conditional dependencies between two or more data sets.

Conditional independence

One assumption with the weight-of-evidence approach is the conditional independence (CI) of evidential maps with regards to the training sites. A pair-wise chi-squared test can be applied and a chi-squared (χ^2) test value calculated for testing CI between binary maps (Bonham-Carter, 1994). Geophysical maps used in this study (aeromagnetic, airborne electromagnetic and horizontal gradient of regional gravity) turned out to be conditionally independent in sufficient level but dependence between till geochemical maps proved to be more complex. The elements of interest (Cu, Fe, As, Te, Ni and Au) were tested against each other. To avoid violation of CI, geochemical anomaly maps of these elements were combined together into one evidence map using the fuzzy logic combination of them as described later in the fuzzy logic section of this paper (Figure 9.).

Table 5 summarizes the pair-wise test of the binary pattern used in final model. With one degree of freedom and probability level of 95%, the test χ^2 value is 3.8 for rejection of the assumption of conditional independence (Bonham-Carter, 1994). Values in Table 5 shows that hypothesis of conditional independence is not rejected at this probability level. Number of occurrences used for χ^2 calculations was 35, which can be too few and cause uncertainty for calculation. Nevertheless, the chi-squared values seem to be insignificant.

The other method for testing CI is the overall test. In the overall test, the total number of occurrences predicted by the model is determined by summation of the product of the area in counts of unit cells times the posterior probability for all cells on the model (Bonham-Carter, 1994). Predicted number of occurrences is usually larger than the observed number. If the predicted number is 10–15% larger than observed, conditional independence between evidential maps may be violated (Bonham-Carter, 1994). In this study, the determined number of predicted occurrences in final model is 42.3, which is 17.3 % larger than the observed number 35. This may indicate some problem with CI, but because χ^2 values does not show any distinct problem between binary pattern of evidential maps and the small number of training points (35) can cause some instability also for overall test, the model was accepted for presentation. A new test for CI (Agterberg and Cheng, 2002) suggests that the conditional independence hypothesis for the current model can be accepted with a probability of slightly less than 90%. The assumption of conditional independence is not required for the logistic-regression method to calculate the posterior probability map. Thus, the logistic-regression method (Agterberg et al., 1993) using the binary generalizations from the weights-of-evidence weights analysis was also calculated to evaluate the possible CI problem. The resulting posterior probability map patterns are similar to the patterns of the weights-of-evidence map. The posterior probability value of the logistic-regression model is on average only 19% lower than the posterior-probability value calculated by the weights-of-evidence method reported here indicating also a minor disturbance in CI.

Table 5. Calculated χ^2 values for testing conditional independence between binary evidence with respect to gold occurrences (35) used in weights of evidence modeling. None of these test statistics are sufficiently high to reject the assumption of conditional independence.

Evidence	Geochemistry	Gravity	Aeromagnetic
Airborne EM	1.64	0.96	1.12
Geochemistry		0.1	0.04
Gravity			0.31

Results and interpretation

Table 6 shows the weights, contrasts and confidences calculated for the model. Confidence values (i.e. the studentized contrast) higher than 2 are considered as ‘acceptable’ (Bonham-Carter, 1994). All evidence used here exceeds this level. Evidential maps can be ranked by contrast for the degree of correlation with the training sites. Horizontal gradient of regional gravity map has the largest contrast value (2.528) indicating that it is the best predictor. The aeromagnetic map is the weakest predictor, but at a contrast of 1.5 is still quite high. The gravity map does not cover the whole study area and there are quite large areas of missing data affecting uncertainty to calculation of posterior probabilities. Twenty-one gold training sites of 35 fall into the pattern from the gravity data. Note that the airborne EM and aeromagnetic maps are the only evidence with W+ significantly larger than the absolute value of W-. The gravity and geochemistry favour the negative side; so they are defining well the areas of poor prospectivity for gold. Whereas the airborne EM and aeromagnetics favour the positive side; so they are defining well the areas of high prospectivity. Thus all the evidence is contributing, but in different ways. The

Table 6. Weights for the binary evidence used for modeling. The total number of training points is 35. Confidence values >2 are considered as 'acceptable'. Prior probability is 0.0009. The unit cell was 0.5 km2.

Evidence	Area [km²]	#Training sites	W–	W+	Contrast	Confidence
Gravity	7928	21	–2.1217	0.4063	2.528	2.4722
Airborne EM	2732	20	–0.6899	1.3671	2.0571	6.0169
Geochemistry	8227	27	–1.0335	0.6028	1.6362	3.8709
Aeromagnetic	1303	9	–0.2254	1.3113	1.5368	3.9681

spatial variation of uncertainty of the posterior probability and its magnitude are shown in Figure 5.

The resulting prospectivity map (Figure 6) highlights the areas being most favorable for greenstone hosted Au–deposits according to the exploration model used. The sensitivity of the model to specific deposits for the modeling was tested by calculating 23 successive models and leaving out one of the deposits in turn. This is a type of jack-knife test. The posterior probability value of each of the model was associated with the deposit point left out from the model and plotted against the posterior probability of the model including all the training sites resulting the scatter plot in Figure 7. The plot suggest that excluding any other deposit from the model, except Kutuvuoma, would not give significant deviation from the model including all the training sites. The reason for different behavior of Kutuvuoma is due to an artifact driven by the generalized gravity pattern including all the other training sites except Kutuvuoma. This leads into an abnormal high negative weight for the gravity pattern when the Kutuvuoma site is excluded because there are then no training sites in the non-favourable gravity pattern. The ArcSDM software arbitrarily assigns a fractional training site when this situation occurs which causes an anomalous low W-. Those training sites plotting below the prior probability (see the close-up in Fig. 7) are all within 600 m from an area with posterior probability higher than prior probability. Another test of the validity of the model can be made by associating the training sites with the modeled posterior probability. Thus, one can estimate how well the model predicts

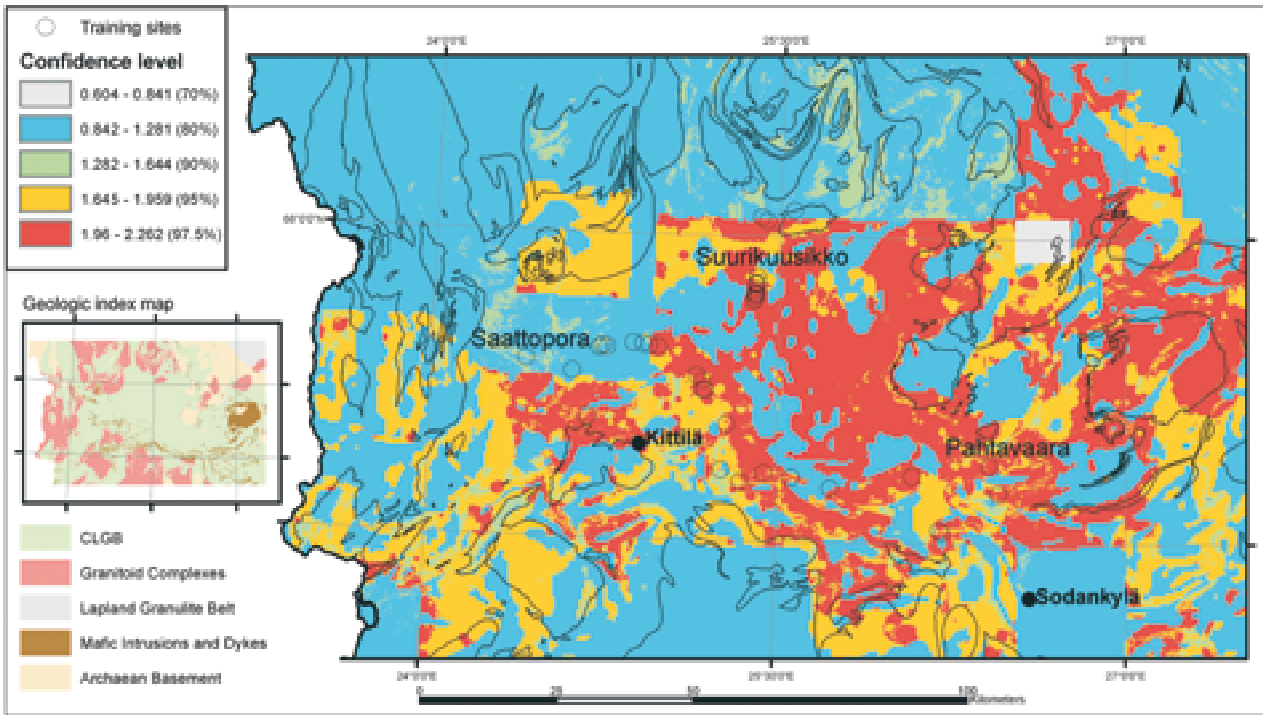

Fig. 5. Map of posterior probability/total uncertainty indicating the spatial variation of confidence that the reported posterior probability is not zero. All the training sites are within the areas that exceed the 80% confidence level. The boundaries of the main lithological units of the geologic index map are shown as black lines in the map, demonstrating that the model excludes most of the non-greenstone rocks as zero posterior probability.

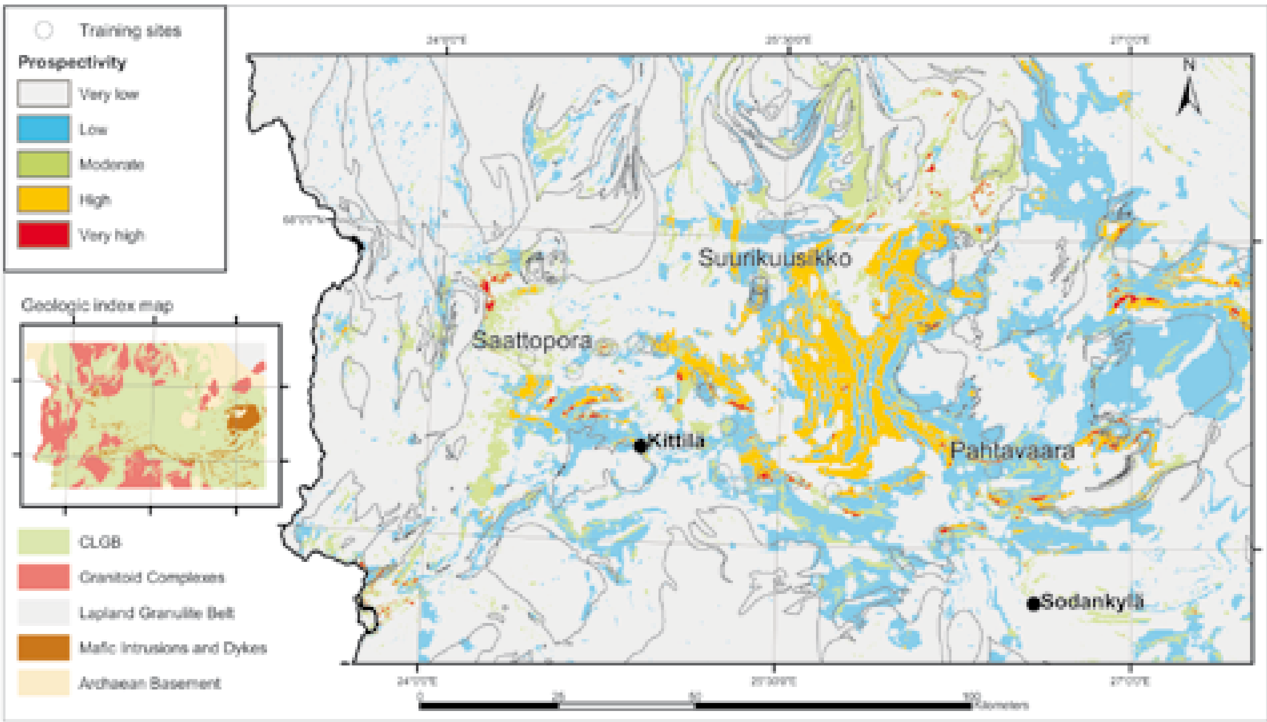

Fig. 6. Weights-of-evidence gold prospectivity map. Posterior-probability model using airborne geophysics, regional gravity and till geochemistry. The lowest class shown in grey represents areas with posterior probability lower than prior probability, which are assumed to not be permissive for greenstone gold deposits. The areas from 'Low' to 'Very high' prospectivity are all above the 80% confidence level as shown in Figure 5. The boundaries of the main lithological units of the geologic index map are shown as black lines in the map. Note that the moderate or higher areas occur only on greenstone rocks.

the training sites. From the total of 35 training sites, 31 are within the classes with posterior probabilities higher than prior probability. If a deposit is considered to occupy an area of 0.5 km^2, which is the unit area used in modeling, the total number of deposits intersecting the classes with posterior probabilities higher than prior probabilities is 35 (i.e. all the training sites) giving perhaps more realistic results. Thus, the model seems to map the training sites reasonably well and one should especially note, that the training sites related to the most significant deposit within the study area found so far, the Suurikuusikko property, also have posterior probability values higher than prior probability falling into the 'high' class in the posterior probability map (Fig. 6).

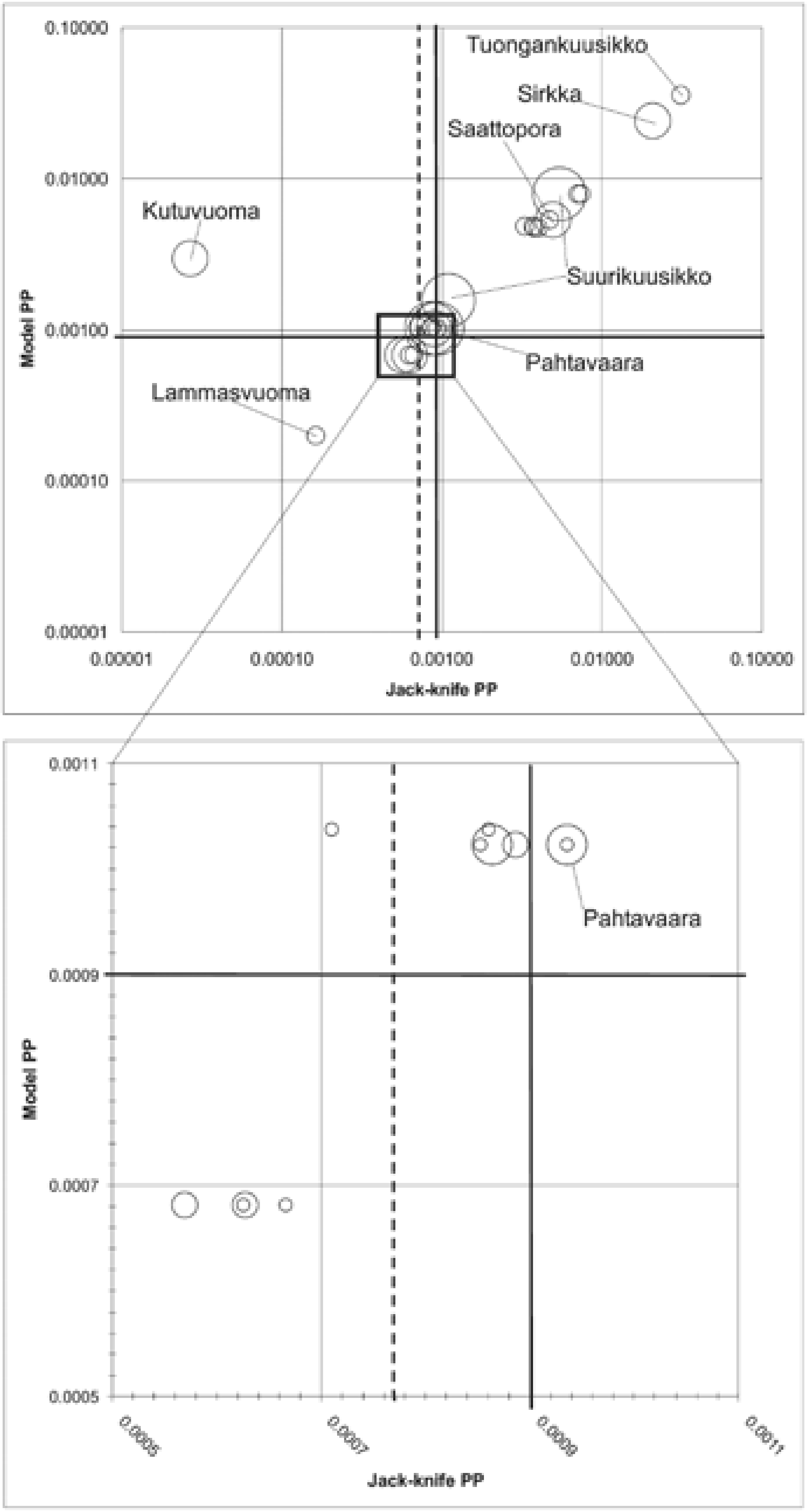

Fig. 7. Results of the jack-knife validation test as a plot of posterior probabilities in the final model and the test models associated with the training sites. The number of training sites used was 35 and prior probabilities varied from 0.0007 (dashed line) to 0.0009 (thick solid line) among the 23 weights of evidence models calculated. The training sites were treated as points in this calculation. The scale in upper plot is logarithmic. The close-up shows posterior probability values from 0.0005 to 0.0017. All the major deposits plot above the prior probability (0.0009).

FUZZY-LOGIC MODELING

First step in fuzzy logic modeling after selecting the appropriate evidential data is to define the relative importance of each of the selected evidential data and assign the fuzzy memberships for the classes of these data. The knowledge of the exploration experts was used to accomplish this task. The assigned fuzzy memberships for each of the evidential data sets are given in Table 7.

The fuzzy membership values were defined after reclassifying the original data by using standard deviation method in ArcView GIS. When reclassifying data using the standard deviations method, ArcView finds the mean value and then places class breaks above and below the mean at intervals of either 1/4, 1/2, or 1 standard deviations until all the data values are contained within the classes. ArcView will aggregate any values that are beyond three standard deviations from the mean into two classes, greater than and less than three standard deviations above and below the mean. In some cases an expert modified the classes manually. The resulting classes were then divided by an expert to be either "anomalous" (fuzzy membership = 1) or "non anomalous" (fuzzy membership = 0) and classes between these two were assigned a linear function between 0 to 1 (Fig. 3). Thus the classification of the data using standard deviation or any other method has a major influence on the final fuzzy membership values. Great care needs to be taken while classifying the data to find the thresholds. Selection of threshold for "anomalous" and "non anomalous" is, however, flexible and is defined by an expert. In Figure 8 all the evidential datasets are displayed according to the fuzzy membership values, red color indicating the significance of the anomaly concerned in each map.

After defining the fuzzy membership values, the evidential data were integrated in several steps according to the exploration model (Figure 8). First the magnetic and resistivity data were combined using a 'Fuzzy AND' operator to define possible conductive alteration zones. Till geochemical evidence was combined in two steps by first integrating metals Fe, As, Te and Ni by 'Fuzzy OR' operator and the resulting map with Cu by using 'Fuzzy AND' operator in order to highlight the anomalies indicating possible sulphide sources. These two intermediate response maps (geophysical and geochemical) were then combined together with regional gravity and Au in till by using 'Fuzzy GAMMA' operator with $\gamma = 0.9$. Since Au tends to have its own characteristics in till, it was used as a single evidence in the final combination as well as the horizontal gradient of the regional gravity, which reflects large crustal structures.

Results and interpretation

The final results are shown as a prospectivity map in Figure 9 classifying the study area based on the relative importance of the integrated datasets. Twenty training sites of 35 fall into fuzzy membership values 0.5 and above, when the training sites are taken as points. Whereas if a training site is surrounded by 600 m buffer representing an area of a site the number is 31 (i.e. 89 %). A significant result is, however, that Suurikuusikko deposit is within the fuzzy membership values 0.7–0.9 suggesting that the current model predicts well Suurikuusikko type of deposit. In addition to good prediction of the known exploration targets, this model also predicts areas with high exploration potential.

Table 7. Thresholds for Fuzzy membership values for the evidential datasets. Classes between these thresholds were linearly transformed to fuzzy membership values between 0 and 1. Each evidence map was reclassified to define classes by the standard-deviation method before the fuzzy membership was calculated. See Figure 3 to understand this process.

Evidence	Not anomalous (0)	Anomalous (1)
Airborne magnetic data (residual nT)	>630	<–270
Airborne EM (Ωm)	>2000	<20
Regional Gravity, horizontal gradient (mgal/500 m)	<1.5	>3.2
Au in till (ppb)	<0.1	>5
As in till (ppm)	<15	>49
Cu in till (ppm)	<48	>116
Fe in till (ppm)	>27610	>57300
Ni in till (ppm)	<62	>129
Te in till (ppm)	<23	>55

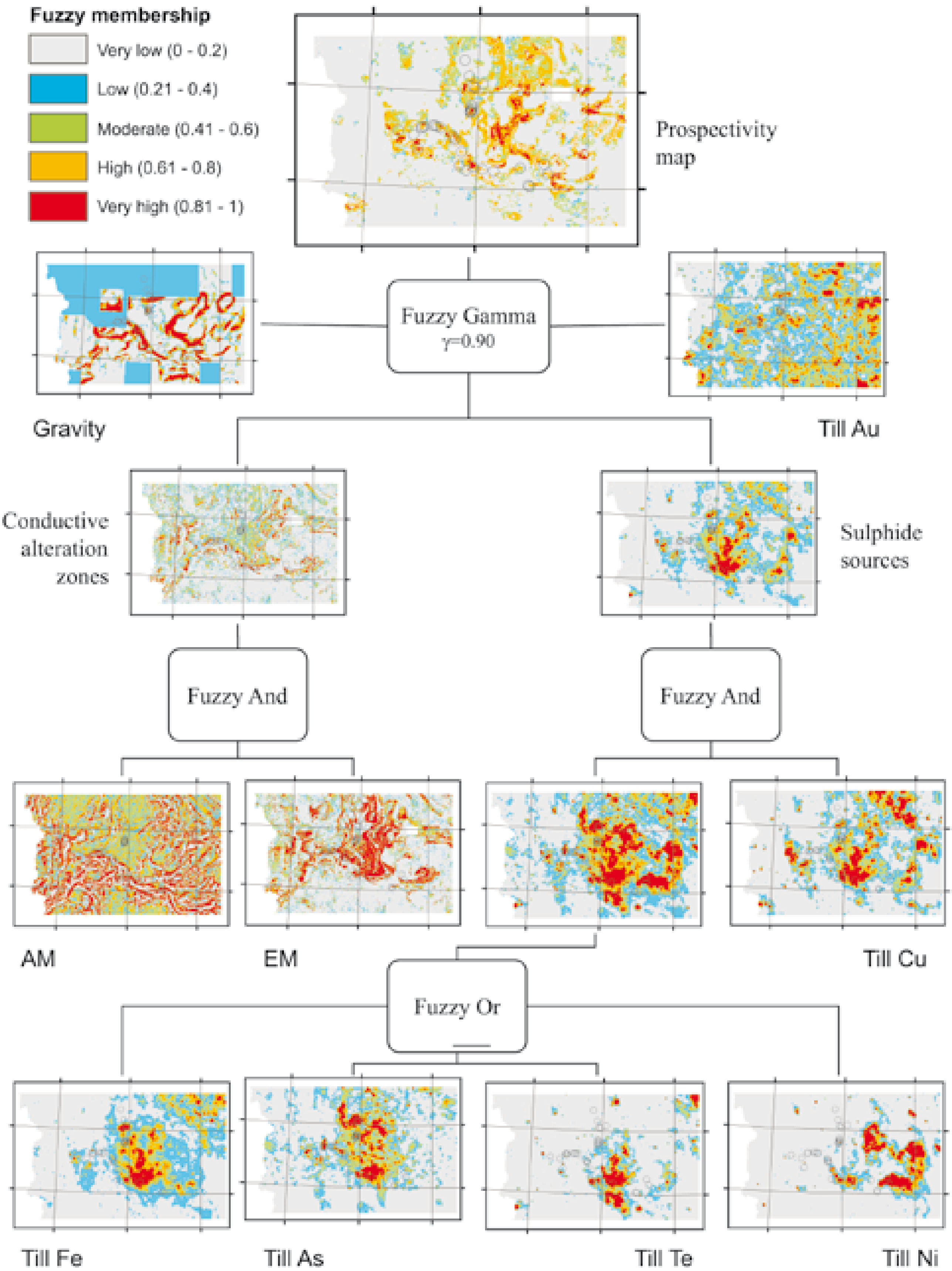

Fig. 8. The inference network of the fuzzy logic model for greenstone-hosted gold deposits. The rounded boxes are the operators (see Table 3 for explanation) and the rectangles represent the evidential data sets and the results.

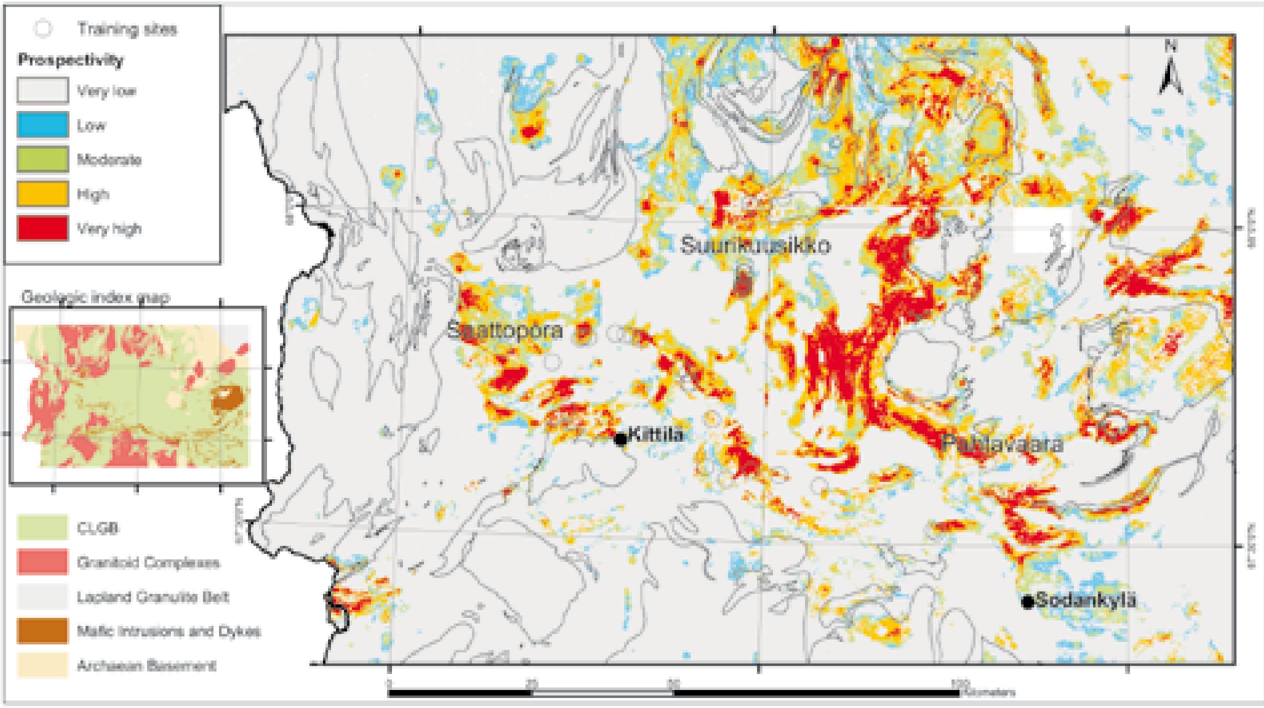

Fig. 9. Fuzzy-logic gold prospectivity map. Fuzzy membership model using airborne geophysics, regional gravity and till geochemistry. The boundaries of the main lithological units of the geologic index map are shown as black lines in the map. Note that most of the non-grey areas are in the greenstone rocks.

DISCUSSION

The aim of the current paper was to make a prospectivity analysis for gold and to test how well the regional datasets of GTK can predict the locations of known deposits. Also the aim was to test the empirical and conceptual approaches. The high-resolution airborne geophysical data would give a chance to interpret spatial models even in greater detail at larger scale than was done in this paper. This would require other evidence as well at the same data resolution and more focused study areas. Comparable data would be local scale geochemical surveys, which would, however, cover only limited areas but would be appropriate data for detailed exploration. For a local scale, a conceptual modeling would perhaps be more suitable since there are seldom statistically enough training points in small areas. The best evidence in the current models was, however, the horizontal gradient derived from the regional gravity data. The large crustal-scale structures seem to have a major control on spatial distribution of Au-deposit within the CLGB. Till geochemistry, which is a widely used exploration tool, is generally a very good data for modeling, but might improve significantly after more elaborate preprocessing than was done here.

In the current weights-of-evidence modeling, all the used training sites were treated as equal or at least being part of the same type common to the greenstone-hosted gold deposits. Each of the occurrences has many unique characteristics, which suggest that they might not be treated as a single deposit style but rather being grouped into several styles resulting in relatively a small number of training sites for each group. As the statistical tests in this paper show, there really is a significant spatial association between the training sites occupying an area of 0.5 km^2 and the specific map patterns used as evidence indicating that all the greenstone-hosted type of Au deposits can be treated as a single group at this scale.

As pointed out by Harris et al. (2001) one should use geostatistical methods to study the spatial behavior of geochemical data before interpolation. This was not done in this study, which might be one reason for a slightly poor predictive capability of the till geochemistry. In addition, the use of geological barriers during the interpolation process might be considered if they are known. Geochemical data is normally found to be a positive type of evidence, not the negative weighting seen here in the weights analyses. This suggests that some other ways of preprocessing the geochemical data should produce better evidence with W+ larger than or at least equal to the absolute value of W- and an increase in the contrast. Similarly, the airborne EM and magnetics are the only evidence with W+ larger than the absolute value of W-. This result for the magnetics was highly enhanced by using the residual from the median filter. Better filtering of the magnetics and useful filtering of the EM should improve definition of the anomalies from these data and increased contrast. Most of the evidential data used here were as far as possible not interpreted data to be able to avoid biased results. However, one might want to use other highly interpreted evidence as well, together with the geophysical and geochemical data, to exploit the results from structural or any other geological modeling providing spatially referenced datasets with sufficient coverage over the area of interest. Example of this kind of data could be paleostress modeling studies (Holyland and Ojala, 1997; Mair et al., 2000, Ojala and Nykänen, 2007), geological shape analysis (Gardoll et al., 2000) or lithodiversity (Mihalasky and Bonham-Carter, 2001). The resolution and coverage of GTK's airborne geophysics and the contrasts found shows that this data is a strong exploration tool. By integrating this high-resolution data together with other less detailed data in GIS environment, as has been done in this paper, one can extract information that would otherwise be difficult to achieve, and laborious and less effective to accomplish.

The calculated weights of evidence and fuzzy logic models (Figs. 6 and 9) visually correlate with each other, which is obviously the result of the more or less identical evidential data used for the models. The agreement between two nominal-scale maps can be estimated by calculating the coefficient of agreement and kappa (Table 8). The overall kappa value for these two models is moderately low (0.22), but the conditional kappa value for the highest class of the two prospectivity maps is 0.66 and 0.48 for the lowest class suggesting that the two models do correlate at both higher and lower probability levels. The moderate levels do not correlate well due to the experts focusing on the thresholds and not assigning the mid point of fuzzy memberships for the evidential data. The moderate values were not considered important in either model, because the ultimate objective was to define the best targets. The area weighted Spearman's correlation coefficient is 0.80 due to the strong correlation between the lowest classes covering a large area in both of the models. Poor correlation between the moderate classes might be overcome with these models by combining the moderate classes. A noticeable point is that the predicted areas are almost entirely within the greenstone belt and in certain formations, even though geological map was not used as input data. Almost all of the predicted areas are within Savukoski and Kittilä groups, which have been suggested to be

Table 8. Matrix of observed proportions (A) and expected proportions (B) of weights-of-evidence (WofE) and fuzzy-logic (Fuzzy) prospectivity models. The values in the matrix are percent of area. Shaded values in principal diagonal represent areas of agreement. Agreement of observed proportions between these models is 60%. and overall kappa value is 0.22. The conditional kappa values for the classes from 1 to 5 are 0.48, 0.01, 0.08, 0.20 and 0.66, respectively. Spearman's area weighted correlation coefficient is 0.80 Calculation procedures after Bonham-Carter (1994). These tables give a measure of the nature of the agreement or correlation between the two models.

A)

	Fuzzy	**Very low**	**Low**	**Moderate**	**High**	**Very High**	
WofE	**Class**	**0–0.2**	**0.2–0.46**	**0.46–0.59**	**0.59–0.71**	**0.71–0.98**	**Total**
Very Low	**<0.0009**	59.46	2.95	3.81	2.29	0.41	68.93
Low	**0.0009–0.00120**	10.51	1.09	2.74	3.52	1.47	19.32
Moderate	**0.00120–0.00748**	2.42	0.26	0.96	1.72	1.00	6.36
High	**0.00748–0.01**	1.07	0.07	0.42	1.29	2.10	4.94
Very High	**0.01–0.03**	0.05	0.00	0.00	0.09	0.31	0.45
	Total	73.51	4.36	7.93	8.91	5.28	100.00

B)

	Fuzzy	**Very low**	**Low**	**Moderate**	**High**	**Very High**	
WofE	**Class**	**0–0.2**	**0.2–0.46**	**0.46–0.59**	**0.59–0.71**	**0.71–0.98**	**Total**
Very Low	**<0.0009**	50.67	3.01	5.47	6.14	3.64	68.93
Low	**0.0009–0.00120**	14.20	0.84	1.53	1.72	1.02	19.32
Moderate	**0.00120–0.00748**	4.68	0.28	0.50	0.57	0.34	6.36
High	**0.00748–0.01**	3.63	0.22	0.39	0.44	0.26	4.94
Very High	**0.01–0.03**	0.33	0.02	0.04	0.04	0.02	0.45
	Total	73.51	4.36	7.93	8.91	5.28	100.00

most favorable for Au within the CLGB area (Eilu et al. 2007). Thus, it seems that both models would pass a rough geological validation. As already mentioned in the Fuzzy-logic section it is promising that the location of the largest known gold deposit, Suurikuusikko, can be predicted by both models. In addition to the already known targets, the models generate new target areas. The region between Suurikuusikko and Pahtavaara seems to give high response in both of the models and is suggested for more detailed and focused modeling. The areas about 50 km to NE from Pahtavaara mine also appear to be highly prospective as well as the area some 25 km NW from Saattopora.

CONCLUSIONS

The spatial modeling techniques tested here proved to give an efficient tool for exploration geologists to integrate data from several geoscientific sources. Conceptual fuzzy-logic method gives a flexible tool to test exploration models on large datasets in an easily understood manner. The uncertainties of the fuzzy-logic modeling can be difficult to estimate, but an expert validation process would in many cases be appropriate and lead to reliable results. Empirical weights-of-evidence method instead includes comprehensive statistical validation process, which makes it laborious but more reliable. Weights-of-evidence method includes better control for uncertainty, but restricts the amount of evidential data to be used due to the requirement for conditionally independence. On the other hand, the weights calculation provides a convenient way to estimate and quantify spatial association between geographical locations like mineral deposits, rock formations etc. and any spatially referenced geoscientific or other relevant data. The agreement between these two models used in this study seems to be good at the low and high prospectivity areas. For future fuzzy-logic models, it seems that expert control of the middle fuzzy membership is also an important consideration, if these mid-range areas of important to the objectives of the modeling. However, the current paper suggests that the fuzzy-logic model produced here could be applied also to a study area without training sites to accomplish a prospectivity analysis within a reasonable confidence level.

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