This thesis comprises a synopsis and six original papers dealing with mineral prospectivity mapping of gold within the Northern Fennoscandian Shield, Finland. Geographical information systems (GIS) with weights-of-evidence, logistic regression, fuzzy logic and neural network models were used in these papers to complete a series of spatial modelling tasks to assess the gold potential of Northern Finland. These results can be used to define regional scale target areas for gold exploration.
SPATIAL DATA ANALYSIS AS A TOOL FOR MINERAL PROSPECTIVITY MAPPING

by

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ACADEMIC DISSERTATION

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Cover: Prospectivity map for orogenic gold mineralization within Central Lapland overlain on digital elevation model. Digital elevation model/lakes and rivers (C) National Land Survey of Finland license number 51/MML/08.

ABSTRACT

This thesis comprises six original papers dealing with mineral prospectivity mapping of gold within Northern Fennoscandian Shield, Finland. Geographic information systems (GIS) enhanced with advanced tools using weights-of-evidence, logistic regression, fuzzy logic and neural network models are used in these papers to complete a series of spatial analysis or spatial modelling tasks for mineral prospectivity mapping. The aim of the thesis is to rank areas within the study area based on their exploration importance, and to compare the different approaches used for modelling and the various applications of these methods.

The deposit types concerned are orogenic gold deposits and iron-oxide-copper-gold (IOCG) deposits. The evidence data used for modelling were derived from high resolution airborne geophysics, regional gravity, regional till geochemistry and 1:200 000 or 1:1M scales bedrock maps. The key parameters used to describe the orogenic gold deposit type were: (i) low magnetic and low resistivity response; (ii) high gravity gradient; (iii) anomalous As, Au, Cu, Fe, Ni and Te in till; (iv) proximity to Sirkka Shear Zone or divergent/convergent stress regimes; (v) paleostress anomaly; and (vi) proximity to greenstone/sedimentary contacts. The derived parameter used to describe IOCG deposits were: (i) proximity to the craton margin; (ii) intersecting fault structures; (iii) presence of granitic intrusions particularly those with compatible and incompatible element enrichment; (iv) Cu, Co and Fe concentrations in till samples; (v) presence of hematite; and (vi) airborne magnetic highs and radiometric U data.

A conceptual fuzzy-logic model was applied for the IOCG prospectivity analysis, whereas several hybrid empirical/conceptual models were used for orogenic gold favourability analysis. The empirical methods were applicable for orogenic gold assessments due to a number of known occurrences of this deposit type within the study area. The results of the modelling were validated by using several statistical validation approaches: jack-knifing, ROC curves, efficiency curves and cross-validation using weights calculation. Field validation was also conducted and indicated good reliability of the models.

The results show that the performance of a prospectivity mapping model is enhanced by adding conceptual derivatives of geological maps in combination with empirical geophysical and geochemical evidence. The study also indicates that weighting of the training sites can used for more realistic ranking of the targets based on their economic value.

Key words (GeoRef Thesaurus, AGI): orogenic gold deposit, IOCG deposit, prospectivity, GIS, weights of evidence, logistic regression, fuzzy logic, neural networks, Central Lapland Greenstone Belt, Fennoscandian Shield, Finland

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“Far better an approximate answer to the right question, which is often vague, than the exact answer to the wrong question, which can always be made precise.”

LIST OF ORIGINAL PUBLICATIONS

This thesis consists of the following six publications referenced using the following designation:


Vesa Nykänen has been the corresponding author for each of the papers and he has been mainly responsible for writing the manuscripts. His contribution in writing papers I and II was 75%. He has written 90% of the papers III, IV and V. Paper VI is 100% written by Vesa Nykänen. He has done all the spatial modelling calculations, data integration and validation of the results. Most of the data pre-processing was done by Vesa Nykänen. Mr. Heikki Salmirinne prepared the geophysical datasets and conducted the jack-knifing models for paper I. Dr. Stephen Gardoll contributed the original idea of preparing one of the derived layers in Paper III. Although all the co-authors helped in writing the papers, Vesa Nykänen as the corresponding author is responsible of all errors in the original papers.
This PhD project developed over a time span between 2003 and 2004. The initial idea of the project was formulated in 2003 during my visit to the U.S. Geological Survey field office in Reno, Nevada. Long discussions on the modelling philosophies and practical issues concerning spatial data analysis or data exploration together with Prof. Gary L. Raines during the lunch breaks at the quad of University of Nevada, Reno (UNR) campus, finally led me to the conclusion that having a closer look on this field of science would be an interesting research project and might also bring results that could benefit the exploration community at large. Although I had planned and initiated the spatial modelling project a little bit earlier, the insights given by Gary Raines helped me to focus more on the spatial modelling methodologies themselves, in addition to the applications of practical mineral potential mapping. The other breakpoint during the project was my visit to Western Australia in 2005, when I had the privilege to collaborate with Prof. David I. Groves, who, on the other hand, introduced me to conceptual targeting and the use of derivatives from a geologic map in mineral prospectivity mapping. Now I had to deal with, not only slightly different terminology (e.g. usage of terms ‘prospectivity mapping’ vs. ‘mineral potential’) and the other nuances of English in these different parts of the world, but also with a slightly different approach to the spatial modelling in general. This made the project not only challenging, but also very interesting and definitely enriched my insights into data exploration. The project was accepted as a PhD project on September 9th, 2006, by the Department of Geosciences, University of Oulu. My supervisors during this project were Dr. Juhani Ojala (Geological Survey of Finland) and Dr. Aulis Kärki (University of Oulu).

1 INTRODUCTION

A geographical information system (GIS) is designed to be used to manage spatially referenced data. It can be used as a tool for making maps or it can be used as a tool for analysing map data, as has been done in this study. Here, a variety of digital geoscientific data from the Geological Survey of Finland (GTK) are used as spatially referenced layers of evidence in mineral prospectivity mapping (also known as exploration targeting or mineral potential assessment), that is, ranking areas according to their exploration importance. Gold exploration has been used as a test case for these techniques demonstrated in this study. This is because of the excellent data coverage within the permissive volcanic belts in northern Finland, and especially because of the dramatically increased activity in gold exploration in Finland and elsewhere in the world within similar geological settings during recent years.

Various GIS methods have greatly surpassed the human brain’s capacity to integrate and analyze quantitatively large amounts of spatially referenced data. However, the human brain is still superior for computing, with its massive number of calculation units (neurons) and interconnections (synapses) leading to a better performance than conventional computers (Zaknich 2003). There are several mathematical and statistical techniques available for recognizing patterns in spatial data, thereby making effective use of the exploration data that grow on an annual basis. This quantitative analysis of spatially referenced phenomena is also called spatial data analysis or spatial modelling, in which the spatial distribution of the observations is taken into account in data analysis and interpretation of the results. The simplest and/or most common functions or operations for spatial data analysis, which are available in most GIS software, include extractions, buffering, overlays, proximity analysis, shortest path calculations, map algebra and raster analysis.

Many of these operations are used in ‘pre-processing’
the original ‘raw’ geoscience data-sets into ‘derived layers’ to be used as inputs in the actual spatial modelling, which aims to provide mineral potential assessments. Figure 1 describes a common workflow in a project using GIS for mineral prospectivity mapping. More or less similar approaches have been introduced by Pan & Harris (2000) and Harris & Sanborn-Barrie (2006). In the initial stage the exploration group may have an expert-knowledge-based exploration model, which can have a scientific background or it can be derived from the practical experience of the geoscientists involved in exploration. Based on this exploration model, the experts then select the data-sets describing the deposit type in question and especially those data best reflecting measurable or mappable features. As a national geological survey, GTK has excellent data coverage of geological, geophysical and geochemical data over the entire country (see e.g. Salminen 1995, Airo 2005). As these data are mostly in digital format, they provide almost infinite possibilities to perform spatial modelling for various geological problems, mineral exploration being only one possible scenario.

After selecting the appropriate and associated data-sets, the most time consuming and critical part of the project begins. Various techniques for pre-processing the data in GIS or any other suitable or required software are used to extract or derive the key features from the raw data. These techniques include image processing, interpolation, raster calculation, rescaling, classification or other so-called ‘geoprocessing’ tasks to prepare the data for the next step, which is the actual data integration part. In this stage, there are various methods available to perform the data integration, and the selection of the method is often based on the data-sets that are available. For example, in an area with known mineral occurrences and deposits, an empirical technique is applicable. After integrating the various input data and their derivatives into a single ‘prospectivity map’, there still remains a very important phase, which is evaluation of the results. Before spending too much time and effort on final field testing which is the most important validation, some statistical testing is required. There are several techniques for validation, and one should carefully consider which approach to select. The selection
of the validation method depends on the modelling technique used and on the mineral occurrence data available. A portion of the known mineral occurrences can be excluded from the training set if there are a reasonable number of sites for both training and validation. If the number of training sites is small, then only one deposit at a time can be left out from a training set in order to make a series of jack-knifing tests. Both of these validation approaches have been used in this study.

1.1 The aim of the thesis

This thesis aims to utilize GIS as a tool for mineral prospectivity mapping (or mineral potential evaluation) via quantitative spatial analysis of various spatially referenced geoscientific data sets. The methods are tested for mapping exploration targets for gold deposits, but they could equally be used to solve spatial problems concerning other natural phenomena or even human behaviour (Way 2003) that could be represented as a map.

This thesis aims to answer the following main research questions:
1. What is the influence of scale or spatial resolution of input data sets in spatial modelling? The spatially referenced geoscientific datasets can be of variable origin and represent a range of spatial resolution. The real world targets that are modelled, however, do have certain specific physical dimensions, which need to be taken into consideration when selecting or collecting the input data for the modelling.
2. How expert-defined conceptual deposit models can be translated into spatial models and how to use conceptual geological evidence in prospectivity mapping? Deposit models define the mineral deposits as distinctive groups with certain descriptive characteristics. The mineral system approach focuses on the processes that operate to form a mineral deposit. Ideally the evidence layers represent the source, migration and depositional processes in the mineral system being modelled. A geological map is a model itself and the derivatives of a geological map used as evidence layers could represent the processes needed to form a mineral deposit.
3. How to validate spatial modelling results? The statistical techniques provide applications to evaluate the modelling results before the field testing. One challenge in validation is the economic aspect of a mineral deposit, which can be a deposit on one day and just an occurrence on another day, when the metal prices are low. Furthermore, a major mining company would have totally different criteria for a prospective area than a junior mining company or a prospector.

In addition to the papers included in this doctoral thesis, the project resulted in several presentations and peer-reviewed extended abstracts in scientific congresses (Nykänen et al. 2005, Nykänen et al. 2006a, 2006b, Ojala et al. 2006, Nykänen & Ojala 2007b, Nykänen et al. 2007, and Ojala & Nykänen 2007a, 2007b). Ojala & Nykänen (2007a, 2007b) used these techniques to evaluate the spatial association between gold deposits and stress anomalies defined by geomechanical modelling. One important aspect of the project has been the help given to the developers of the Spatial Data Modeller (SDM) software (Sawatzky et al. 2007) by beta testing of the code used for modelling. During the testing, a few ideas for improving the software and showing how things could be done better arose. An example of an improved approach, which was finally implemented in SDM, is for assigning fuzzy membership values for ordinal data by utilizing the classification methods of ArcGIS software. First a dataset of a continuous variable is classified by using one of the common classification techniques in ArcGIS (i.e. equal intervals, quantiles, standard deviations etc.), and then the ordinal class numbers are divided by the number of classes resulting from the reclassification. This results in linear transformation of the ordinal class numbers into fuzzy membership values in the range [0, 1].

1.2 Methodology

The commercial GIS packages ArcView GIS 3.2 and ArcGIS 9.2 from ESRI, enhanced with advanced public-domain extensions or add-ons called ArcSDM (Kemp et. al. 2001, Sawatzky et al. 2004) and SDM (Sawatzky et al. 2007), were employed in this study to create assessment of mineral potential within a geological terrain that is known to be permissive for gold (e.g. Eilu et al. 2007). The gold deposits have been classified, by taking into account certain measurable features, into either orogenic gold or iron-oxide Cu-Au (IOCG) deposits. The main assumption is that these features need to be displayed on geological, geophysical or geochemical maps which are relevant to each type of gold mineralization.

Map scale is an important feature for many aspects of spatial modelling. The data sets collected may have
different spatial resolutions and the spatial phenomena being modelled may have different dimensions, shapes and orientations. For example, orogenic gold deposits and alteration haloes are typically thin (a few metres or tens of metres) and long (a few hundreds of metres) and thus could be difficult to either detect in airborne geophysical surveys or recognize in low sampling density geochemical surveys. This fact must be considered when preparing the data, as described below.

The map can be presented in either vector or raster form. Depending on the techniques and software used, they might need to be transformed in raster format using a specific pixel, or cell, size, for the modelling purposes, as was done in this study. The selection of the cell size depends on the scale of the input data, both the evidence maps and the target (e.g. deposit) dimensions. The selection of the cell size must also take into account the target size being modelled, so that one individual cell could only include one target. If the cell size is much smaller than the targets with certain directions, then several adjoining cells or pixels may be required to represent each of such targets. This was done in Papers I, II, III and VI, where some of the training sites for orogenic gold deposits were represented as several adjoining cells along strike of elongated gold deposits (e.g. Suurikuusikko).

Prior to the era of modern GIS, which started in the 1990’s, pioneers developed statistical methods and spatial analysis for mineral resource assessment (e.g. Agterberg 1984). Later, these methodologies were applied in Finland for evaluation of mineral resource potential and exploration target selection (Gaál 1984, 1988, 1990). In 1988, the International Association for Mathematical Geology (IAMG) organized a symposium called ‘Computer Applications in Resource Exploration’ in Helsinki, Finland. This symposium attracted 75 scientists from 16 countries and resulted in a book of papers describing applications to prediction and assessment for metals and petroleum (Gaál & Merriam 1990). More recently, the annual conference of IAMG in Toronto, Canada, in 2005 titled ‘GIS and Spatial Analysis’ produced about 300 scientific presentations and a conference proceedings book with 1345 pages (Cheng & Bonham-Carter 2005), indicating the significant increase in the number of scientists working in this field.

There are many different methods available for spatial modelling applied to mineral prospectivity mapping, and the selection of a specific technique is often made depending on the data that are available. Bonham-Carter (1994) divides these spatial modelling methods into two main groups based on the approach: data and knowledge driven. For ‘brown-fields exploration’ in mature mineral exploration terrains, where abundant data are available and many mineral deposits are already known, an empirical (or data-driven) approach is very often applicable. In techniques for empirical spatial modelling, known mineral deposits are used for ‘training’ the model, for example, (a) to define appropriate thresholds for geophysical and/or geochemical data or (b) to answer the question ‘how close is close?’ if proximity to certain mapped features is considered favourability criterion for the mineralization type concerned. These data-driven techniques include weights of evidence (Venkataraman et al. 2000, Carranza & Hale 2000, Harris et al. 2000, 2001, Raines & Mihalasky 2002, Paganelli et al. 2002, Cheng 2004, Carranza 2004, Kapo & Burton 2006, Raines & Bonham-Carter 2006, Harris & Sanborn-Barrie 2006), logistic regression (Agterberg 1974, Chung & Agterberg 1980, Reddy et al. 1990, Harris & Pan 1999, Sahoo & Pandalai 1999, Carranza & Hale 2001b, Robinson et al. 2004) and artificial neural networks (Harris & Pan 1999, Koike et al. 2002, Bougrain et al. 2003, Brown et al. 2000, 2003, Porwal et al. 2003b, 2004), which were all also used in this study. A novel unsupervised empirical (or data driven) technique called self organizing map (SOM) or Kohonen’s map (Kohonen 1995) is also available. Bierlein et al. (2008) give an example of using SOM for clustering and classifying multivariate data.

In cases where there are no known occurrences of the deposit type being modelled or the number of the deposits is too low to make valid statistical calculations, a conceptual (or knowledge-driven) approach can be used. In techniques for conceptual spatial modelling, expert opinions are used to define the thresholds. The knowledge-driven techniques include applications of fuzzy logic (An et al. 1991, D’Ercole et al. 2000, Knox-Robinson 2000, Carranza & Hale 2001a, Porwall et al. 2003a, Luo & Dimitrakopoulos 2003, Tangestani & Moore 2003, Rogge et al. 2006), evidential belief function (Moon 1990), the Dempster-Shafer model (Tangestani & Moore 2002, Rogge et al. 2006) and the decision tree approach (Reddy & Bonham-Carter 1991). Some authors, on the one hand, have also combined different approaches and produced hybrid models (e.g. Brown et al. 2003, Porwal et al. 2004, 2006), as has been employed in this thesis research. Carranza & Hale (2002), on the other hand, demonstrate a data-driven approach of using evidential belief functions, which are usually applied in knowledge-driven approaches to mineral potential mapping.

Even though the spatial modelling techniques can be roughly divided into these two groups, the individual approaches are not necessarily purely empirical or
conceptual. For example, when conducting empirical weights-of-evidence modelling, objective expert decisions are made in selecting the training sites or evidence data to be used. Furthermore, fuzzy input layers can be used as evidence in an empirical modelling technique (e.g. Brown et al. 2003), and expert input is brought into the modelling in that way. In cases where minimal expert input takes place, purely empirical spatial modelling techniques would actually fit into the category of spatial data mining (Miller & Han 2001), which is a field where vast spatial databases are analyzed to find unexpected correlations or patterns within the data. SOMs are prime examples of data mining techniques.

1.3 Study area

This thesis comprises six original papers that are based on studies within three different study areas located in northern Finland (Fig. 2). Paper IV covers the largest area, whereas Paper II is focused on a relatively small area within the study area of Papers I, III, V and VI. The bedrock of these areas is part of the Fennoscandian Shield, which is composed mainly of Archaean granite-gneiss-greenstone terrains and covering Palaeoproterozoic schist belts (Vaasjoki et al. 2005). The study areas of Papers I, II and VI belong to one of the Palaeoproterozoic greenstone belts, namely the Central Lapland Greenstone Belt (CLGB), located in the northern part of the Fennoscandian Shield.

The Fennoscandian Shield (Fig. 3), which is the north-westernmost part of the East European Craton, can be divided into four areas: the Archaean, the Svecofennian and Sveconorvegian domains, and the Transscandinavian igneous belt between these domains (Vaasjoki et al. 2005). The Archaean bedrock in the Fennoscandian Shield is divided into three adjacent cratonic nuclei, Norrbotten, Karelia and Kola. These nuclei were fragmented between 2.51 and 2.4 Ga, and finally amalgamated by ca. 1.9 Ga (Lahtinen et al. 2005). Between 1.9 and 1.8 Ga, a number of juvenile volcanic arcs and micro-continents were accreted to the Archaean craton, mostly on its south-western margin. This resulted in the formation of the present Fennoscandian Shield through cratonisation by 1.77 Ga (Lahtinen et al. 2005). Eilu et al. (2007) consider these epochs as significant events for gold mineralization in northern Finland.

The Central Lapland Greenstone Belt (CLGB) is located in the Northern Fennoscandian Shield, approximately 100 km north of the Arctic Circle (Fig. 4). It is mainly composed of Palaeoproterozoic mafic to ultramafic volcanic sequences and related sedimentary
units surrounded by granitic intrusions (Lehtonen et al. 1998). There are more than 30 drilled gold occurrences within this area (Eilu 1999, 2007). Two of these have been mined (Saattopora mine during 1988–1998 and Pahtavaara mine during 1996–1999 and 2002–2007) from the late 1980s up to the present. The third gold mine within the CLGB will be the Kittilä mine, which will exploit the orogenic Suurikuusikko gold deposit, currently under development and commencing gold production in 2008.

Geologically, the CLGB consists of Palaeoproterozoic volcanic and sedimentary cover (2.5–1.97 Ga) on the Archaean granite gneiss basement (3.1–2.6 Ga) (Hanski & Huhma 2005). The Kittilä greenstone belt, hereafter the Kittilä Group, is suggested to be alloctonous (Hanski 1997), whereas the rest of the belt is...
considered to be autochthonous or paraautochthonous (Hanski & Huhma 2005).

The Salla Group is the lowermost lithostratigraphic unit within the CLGB, comprising intermediate to felsic volcanic rocks with clearly visible and recognizable volcanogenic extrusive structures (Hanski & Huhma 2005). The overlying volcanic rocks of the Onkamo Group lie in places directly on top of the Archaean basement. These volcanic rocks are mainly mafic to intermediate lavas including andesites and fragmental ultramafic rocks including komatiites. The volcanic formations of the Salla and Onkamo Groups are followed by the epiclastic sedimentary sequences of the Sodankylä Group. These rocks are

Figure 4. Lithostratigraphic map of the Central Lapland Greenstone Belt and its surroundings after Lehtonen et al. (1998). Orogenic gold occurrences are marked with yellow dots, gold mines with a larger symbol. The mines are also labelled in the map as are the major structures, the Sirkka Shear Zone (SSZ) and the Kiistula Shear Zone (KiSZ) (Patison 2007).
mainly orthoquartzites, sericite quartzites and mica schists, with minor inter-bedded carbonate rocks and mafic volcanic rocks, deposited on top of the Archaean basement or the volcanic successions of the Salla or Onkamo Groups. The clastic metasedimentary rocks of the Sodankylä Group are overlain by fine-grained metasedimentary rock including phyllites, black schists and mafic tuffitic rocks of the Savukoski Group. Primitive komatiitic or picritic volcanic rocks of the Sotkaselkä and Sattasaara formations overlie these metasedimentary units. The largest volcanic formations within the CLGB, and within the Fennoscandian Shield, belong to the Kittilä Group, which is dominated by mafic metavolcanic formations with tholeiitic affinities. Among the extensive volcanogenic formations there are also several sedimentary interbeds of metagraywackes, phyllites, graphite- and sulphide-bearing schists and carbonate rocks.

The volcanic successions of the Kittilä Group are overlain by clastic metasedimentary rocks of the Lainio and Kumpu Groups. These comprise meta-arkoses, quartzites, polymictic meta-conglomerates and metasiltstones. Mafic plutonic rocks of several age groups intrude the sedimentary and volcanic sequences of the CLGB. These include 2440 Ma layered mafic intrusions (Mutane 1997), ca. 2220 Ma differentiated sills, also known as gabbro wehrlite association (Hanski 1987), and ca. 2050 Ma mafic intrusions (Mutane 1997). Hölttä et al. (2007) describe several metamorphic zones within the CLGB. They conclude that metamorphism was related to tectonic thickening during overthrusting of the Lapland Granulite Belt to the south, but the rocks of the belt may be overprinted by later, postmetamorphic faulting and folding. Most of the known orogenic gold occurrences of Central Lapland are located within the greenschist facies zone defined by Hölttä et al. (2007).

1.4 Deposit types

Although the spatial modelling techniques described in this thesis were tested and used for several purposes during the project, those most relevant to reconnaissance or regional-scale gold exploration were selected for the papers included in the thesis. Two main gold deposit types have been proposed for the gold occurrences in Northern Finland. These two deposit types, orogenic gold and iron-oxide-copper-gold (IOCG), are briefly described below.

1.4.1 Orogenic gold deposits

Based on the summary by Weihed et al. (2005), the orogenic gold deposits in the Fennoscandian Shield have similar features to orogenic gold deposits worldwide (Groves et al. 1998, McCuaig & Kerrich 1998, Goldfarb et al. 2001). They are structurally controlled, being located in second- to lower-order shear or fault zones within local compressional to transpressional structures at the time of mineralisation. The FinGOLD database (Eilu 1999, 2007) includes over 30 drilled gold occurrences with at least one metre of one ppm Au within the CLGB.

The orogenic gold deposits within the CLGB are spatially related to multi-stage alteration zones. The alteration styles reported are sericite and carbonate alteration in lower-to-middle greenschist facies domains, biotite and carbonate alteration in upper-greenschist to lower-amphibolite facies domains, and biotite alteration and formation of K-feldspar and calc-silicate minerals in higher metamorphic-grade domains (Eilu & Weihed 2005). The breakdown of magnetite due to hydrothermal alteration is the most prominent and detectable feature in magnetic-field total intensity maps (Airo 2002). Table 1 summarises the mappable predictive variables used for describing orogenic gold deposits (Nykänen & Salmirinne 2007, Nykänen et al. 2008b).

Table 1. Mappable predictive variables used for describing orogenic gold deposits (Nykänen & Salmirinne 2007, Nykänen et al. 2008b).

<table>
<thead>
<tr>
<th>Evidence</th>
<th>Data origin</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Empirical</strong></td>
<td>Low magnetic and low resistivity response</td>
</tr>
<tr>
<td>Alteration zones</td>
<td>High gravity gradient</td>
</tr>
<tr>
<td>Large crustal structures</td>
<td>Anomalous Fe, Co or Cu in till</td>
</tr>
<tr>
<td>Sulphide mineralisation</td>
<td>Anomalous Au in till</td>
</tr>
<tr>
<td>Gold mineralisation</td>
<td></td>
</tr>
<tr>
<td><strong>Conceptual</strong></td>
<td>Density of lithological contacts</td>
</tr>
<tr>
<td>Lithodiversity/complexity</td>
<td>Proximity to SSZ or divergent/convergent stress regimes</td>
</tr>
<tr>
<td>Strain gradients particularly around granitoids</td>
<td>Paleostress modelling using UDEC</td>
</tr>
<tr>
<td>Dilatational sites</td>
<td>Proximity to greenstone/sedimentary contacts</td>
</tr>
<tr>
<td>Rheology contrast/seals</td>
<td></td>
</tr>
</tbody>
</table>
1.4.2 Iron-oxide Cu-Au (IOCG) deposits

The northern region of the Fennoscandian Shield is recognised as an economically important metallogenic province dominated by generally small, Fe-oxide and Au-Cu deposits, some with IOCG affinities (Weihed et al. 2005). These deposits mainly occur within, or close to (<100 km), the margin of the Archaean craton (Fig. 3), above Archaean continental crust and subcontinental lithospheric mantle, and are hosted by juvenile Palaeoproterozoic volcano-sedimentary sequences formed during rifting of the Archaean craton (Weihed et al. 2005).

IOCG deposits were originally defined as an individual mineral deposit type by Hitzman et al. (1992) after discovery and research on the Olympic Dam deposit in the Gawler Craton of South Australia (Oreskes & Einaudi 1990, 1992). The IOCG deposit type includes deposits enriched in iron oxides, some of which contain Cu and Au. Some of the IOCG deposits contain only Cu or Au and yet others are iron oxide-rich deposits with accessory P (e.g. Kiruna) or REE (e.g. Bayan Obo). In this thesis, IOCG is used as a term to describe those deposits placed in the broader grouping that are iron oxide-rich deposits with significant Cu-Au grades.

The features of IOCG deposits that are visible in geological, geophysical and geochemical maps are: 1) proximity to craton margin; 2) proximity to intersections of fault structures; 3) presence of granitic intrusions, particularly those that may be enriched in both compatible and incompatible elements; 4) magnetic highs related to magnetite concentrations in the deposit; 5) high-U radiometric signatures; 6) presence of hematite; and 7) anomalous Cu, Au or Fe and incompatible elements associated with mineralization. Table 2 summarises these mappable predictive variables used for describing IOCG deposits (Nykänen et al. 2008a).

### Table 2. Mappable predictive variables used for describing IOCG deposits (Nykänen et al. 2008a).

<table>
<thead>
<tr>
<th>Evidence</th>
<th>Data origin</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Geology</strong></td>
<td></td>
</tr>
<tr>
<td>Proximity to craton boundary</td>
<td>Interpreted from several sources (geology, geophysics and geochemistry)</td>
</tr>
<tr>
<td>Proximity to Kainuu suture</td>
<td>1:1M scale bedrock map</td>
</tr>
<tr>
<td>Density of lineaments</td>
<td>1:1M scale bedrock map + interpretations from airborne geophysics and digital elevation model; density of the features in 20 km search radius</td>
</tr>
<tr>
<td>Proximity to igneous activity (1.9 – 1.7 Ga)</td>
<td>1:1M scale bedrock map</td>
</tr>
<tr>
<td>Proximity to hematite showings</td>
<td>Mineral occurrence database</td>
</tr>
<tr>
<td><strong>Airborne geophysics</strong></td>
<td></td>
</tr>
<tr>
<td>Proximity to airborne magnetic anomalies</td>
<td>Low altitude airborne geophysics</td>
</tr>
<tr>
<td>U radiation anomalies</td>
<td>Low altitude airborne geophysics</td>
</tr>
<tr>
<td><strong>Till geochemistry</strong></td>
<td></td>
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<tr>
<td>Incompatible elements</td>
<td></td>
</tr>
<tr>
<td>Ba, K, La, Li, P</td>
<td>‘Regional till’ geochemistry (1 sample/4 km²)</td>
</tr>
<tr>
<td>Th, U</td>
<td>‘Atlas till’ geochemistry (1 sample/300 km²)</td>
</tr>
<tr>
<td>Compatible elements</td>
<td></td>
</tr>
<tr>
<td>Cr, Ni, Ti</td>
<td>‘Regional till’ geochemistry (1 sample/4 km²)</td>
</tr>
<tr>
<td>Sulphides</td>
<td></td>
</tr>
<tr>
<td>Co, Cu, Fe</td>
<td>‘Regional till’ geochemistry (1 sample/4 km²)</td>
</tr>
</tbody>
</table>

2 REVIEW OF THE ORIGINAL PAPERS


In this first paper, the regional-scale geophysical and geochemical data sets were used to create two prospectivity models for orogenic gold deposits within the Central Lapland Greenstone Belt. The first model is based on the empirical weights-of-evidence method and the second on the conceptual fuzzy-logic method. The data used were derived from a high-resolution airborne magnetic and electro-magnetic survey, regional gravity survey, and regional scale multi-element till geochemical survey. The validation...
of the weights-of-evidence modelling was conducted by initially leaving out one of the training sites and comparing the results with the original model using all the training sites. To avoid the consequences of conditional dependency, the geochemical data were pre-processed, so that the individual elements used were combined in a fuzzy-logic model together with the other elements used as indications of gold mineralization and sulphide sources.

The comparison of the resulting prospectivity maps from these two different methods show, that they correlate well in both high and low probability areas. The lack of correlation in intermediate probability areas might be due to poorly defined mid-points of fuzzy membership values for the evidential data. However, most of the favourable areas based on these two models are within the Savukoski and Kittilä Groups, which are the stratigraphic units suggested being most favourable for gold deposits within the CLGB (Eilu et al. 2007).

This paper concludes that the fuzzy logic method is a flexible tool for testing exploration models. The weights-of-evidence method instead provides a comprehensive statistical validation process, and the weights calculation is a convenient way to estimate and quantify spatial associations between geographical locations, including mineral deposits, rock formations, and any spatially referenced geoscientific or other relevant data.


A previously published study by Raines & Mihalasky (2002) showed that spatial analysis using small-scale geologic map data (1:2M) can reproduce mineral assessments made with larger scale data. The aim of the second paper in this thesis is to quantify the effects of the scale of the geophysical data used for spatial modelling. This was done by reducing the spatial resolution of high-resolution airborne magnetic data. The study area for this test measures 2600 km² within the central part of the CLGB, which was covered by two airborne surveys completed in 1979. The flight direction was east-west, line spacing was 200 m, and terrain clearance was 30–40 m.

The original magnetic field total-intensity data were upward-continued to produce a series of grids of aeromagnetic data at six different spatial resolutions. In this way, various flight altitudes were simulated from the original flight altitudes of 30 to 2000 m. The grid cell size was also increased gradually from 50 to 1600 m. In addition to the ‘raw’ data, a median filter was also applied. The median filter was calculated by subtracting from the raw aeromagnetic data the median value of a four km radius, circular neighbourhood around each of the cells within the grid to produce a magnetic residual. The same routine was applied for each upward-continued grid. This study shows that discovering small gold deposits is sensitive to the flight direction and flight altitude. When the simulated flight altitude is above 200 m, the grid values do not satisfactorily reflect patterns indicating the locations of the gold targets and the grid values approximate a random distribution pattern. This paper also suggests that the measure of Moran autocorrelation could be used to test the quality of the aeromagnetic data for predicting exploration targets.


Paper III describes a technique of using empirical geophysical and geochemical data from Paper I, together with new conceptual geological data sets, to assess mineral potential for orogenic gold deposits within the CLGB. The conceptual evidence maps are derived from a 1:200 000 scale litostratigraphic bedrock map. The spatial modelling techniques in this paper include a combination of fuzzy logic, weights-of-evidence and logistic regression, so this is a hybrid model. The last technique was used to overcome the consequences of conditional dependencies caused by the use of the new evidence layers. The geological units in the bedrock map used in this study are mostly reflected by the airborne magnetic map and thus these two layers correlate markedly. The resulting prospectivity maps are validated by leaving out a random subset of the training sites and comparing their location with respect to the prospectivity map. This was done by calculating the weights for each model by using the validation sites. Another validation test used in this study was efficiency curves (Chung & Fabbri 2003). Both validation methods indicate that the new combined conceptual/empirical modelling performed slightly better than the original ‘pure empirical’ model of Paper I.


This paper is an example of how expert-defined
mineral deposit models can be created, documented and tested by using conceptual fuzzy logic modelling. In comparison to the other models used in this thesis, this one is purely based on expert opinions and no statistical analysis was performed to define the thresholds for the uni-element geochemical data or for the geophysical, geological or other evidence. All input data were rescaled from zero to one according to their exploration importance as defined by experts. A value of zero or close to zero indicates low exploration importance while a value of one or close to one indicates high exploration importance within the particular map pattern. The methodology is based on fuzzy-set theory (Zadeh 1965), which was later adapted to mineral potential assessments by Bonham-Carter (1994). Altogether, 20 different maps derived from geochemical, geophysical and geological data were combined in a complex inference net to produce a single prospectivity or favourability map for IOCG deposits. The study area was defined to cover the Archaean craton areas within Finnish borders. The resulting prospectivity map was then statistically validated by calculating weights for proposed deposits with IOCG affinities within the study area. Most of these deposits lie within the conceptually predicted target zones. The recently confirmed IOCG deposit at Kolari (Niiranen et al. 2007) is sited within a high favourability area in the IOCG prospectivity map.

Due to a mistake within the final stage of preparing the manuscript, a wrong version of Figure 1 was printed and published in Paper IV. However, the correct one was used in the proofs, which were evaluated by the two reviewers. The correct map, enhanced with data showing the location of main gold deposits within the Fennoscandian Shield, is presented as Figure 3 in this synopsis.


This paper is a short summary of the first stages of the field evaluation of the orogenic gold prospectivity models in Papers I and III. The field testing was done by sampling of outcrops within a highly favourable area and also by re-sampling a drill core that intersected another highly favourable area. Statistical validation was done by using 11 gold prospects, which were not used for training but were introduced as validation sites in this paper. The current exploration activity in terms of exploration licenses issued for gold exploration within the study area was also used for validation. This study does not show if the models described in this thesis have initiated gold exploration, but it indicates a clear correlation between the new claims and the high prospectivity areas of the published models. The field tests indicate elevated gold and tellurium values within the high prospectivity area.


The last paper utilizes a novel technique of using artificial neural networks (ANN) in data analysis. This was done by using a supervised ANN called a radial basis functional link net, a technique requiring both examples of known targets as well as examples of locations where the desired targets are known not to occur. The deposit sites were the known orogenic gold deposits within the CLGB and the non-deposit sites were other deposit types within the same area. The number of deposit and non-deposit sites was kept equal. The evidence data layers were the same as those used in Paper III. For the ANN analysis, the data were presented as n-dimensional feature vectors, where the dimension was defined by the number of input layers.

The effects of variable cell size (i.e. spatial resolution), variable classification (i.e. data reduction), and weighted training were tested by conducting a series of models, and validation of the models was achieved using a random selection of deposits and non-deposits sites and using receiver-operator-curve methodology. This study shows that increasing the cell size (i.e. decreasing spatial resolution) deflates the performance of an RBFLN less than generalization of inputs into fewer map classes. By assigning weights to the training sites in order to rank them based on their most important exploration properties (e.g. deposit size), the classification of the outputs of an ANN can be fine-tuned. Comparison with the models described in Papers I and III was also completed. It is concluded that RBFLN performs better than weights-of-evidence or fuzzy logic models, and equal to logistic regression with identical inputs, when evaluated in terms of the area under curve (AUC) measure of receiver operating characteristic (ROC) curves.
Hronsky & Groves (2008) consider exploration targeting as a high-level scientific discipline at the pinnacle of scientific endeavour in applied economic geology. This statement is well supported by the annually growing number of papers related to exploration targeting or mineral prospectivity mapping and GIS-based spatial modelling applied to geosciences in general. This trend is also seen in the appearance of special publications about this discipline (Harris 2006, Raines & Bonham-Carter 2007, Groves 2008). The spatial modelling techniques for mineral prospectivity mapping are evolving rapidly together with the evolution of GIS software and computer technology. According to Haykin (1994), the neurons of a human brain, on the one hand, were five to six orders of magnitude slower than silicon logic gates of computers in 1994 but, on the other hand, human brains have a huge number of neurons and interconnecting synapses, such that they are enormously effective in contrast to processing units of modern computers. This gap narrows down each day with the evolution of computer technology, but human brains do still manage to perform better than artificial intelligence (Zaknich 2003). However, there are tasks that are more suitable for computers than for a human brain to compute, like counting millions of cells on a map. The advantage of using a computer is that it can be solely focused on the given task. An artificial neural network (ANN) is, according to Haykin (1994), a massively parallel distributed processor with a natural tendency for storing experiential knowledge by using a learning process and synaptic weights for storing the knowledge. The ANNs can perform brain-like behaviours such as learning, association, categorization, generalization, feature extraction or optimization (Zaknich 2003).

Even though the application of neural networks in geosciences is still relatively rare, they are widely used in engineering sciences (e.g. Haykin 1994, Looney 1997, Tsoukalas & Uhrig 1997, Zaknich 2003 and references therein). The selection of methods for individual tasks is profoundly and eventually dependent on the data available for a given problem. In data-rich circumstances, empirical methods like weights of evidence or neural networks can be used, whereas in data-poor or under-explored areas, conceptual techniques are more applicable. The latter are especially useful if there are good theories; for example, exploration models that can be used to define the key parameters for the model. Nevertheless, between these two end-members are the hybrid techniques, which employ several methods or a combination of them, as has been done in this thesis where the weights-of-evidence method was used together with logistic regression and fuzzy logic. Another example of a hybrid method is given by Brown et al. (2003), who used conceptually-defined fuzzy-membership input layers in an empirical neural network method. Hronsky & Groves (2008) underline that hybrid models are eventually the reality in spatial modelling and are more commonly used than purely empirical or purely conceptual models.

The evidence data sets used for the derived layers in spatial modelling are both empirical and conceptual in nature. The high-resolution airborne geophysical data, on the one hand, provide indirect indications for the presence of gold mineralization by showing the alteration zones related to the mineral deposits. The regional till geochemistry, on the other hand, provide both direct indication (Au and elements indicating sulphides) and indirect indication (elements indicating alteration) for the presence of gold mineralization. However, because the density of sampling the uneven and multilayered regional till cover is so sparse, the pathfinder element distribution in till was not taken as exclusive evidence. This explains why the Hanhimaa area (e.g. Eilu 2007) is not classified as a high prospectivity area when the regional till geochemical data were used. The conceptual evidence used (i.e. data derived from geological maps) can give more geological input into the models in terms of structural interpretations, age relations, lithological control, rheology contrast, and conceptual key parameters defined by the experts, some of which are difficult or impossible to define from purely empirical data. A geological map is here considered as highly conceptual data, a model itself, because it is based on integration and combination of empirical observations and geophysical or geochemical measurements. By adding the derived geological parameters, the predictive power of the models is enhanced, even though some conditional dependency was introduced. This conditional dependency was overcome by using techniques, for example, logistic regression and neural networks, which are not affected by this problem.

Selection of training sites is probably the most critical expert decision in all empirical methods used for spatial modelling. The classification of the mineral deposits used as training sites might not be precise and the location of the sites within the database may be incorrect. Nevertheless, the spatial modelling techniques can help in mineral deposit classification. It is not easy to classify mineral deposits into distinct groups. Commonly, they rather belong to a continuum between end members. The diverse IOCG deposit
type is a good example of this kind of mineral deposit classification. The consequence is that, in modelling, it is challenging to make an exploration model that can describe the IOCG deposits so that their distinctive characteristics are represented in map patterns. However, sometimes the modelling shows that the classification used is questionable, when some deposits tend to be highly different from other deposits classified in the same group. An example of this is the Pahtavaara gold deposit in Central Lapland. This deposit does not seem to fit in the class of orogenic gold deposits as well as the other deposits within the area. The Pahtavaara deposit has been re-classified recently as most probably a metamorphosed seafloor hydrothermal system rather than an orogenic gold deposit. This conclusion is based on its coarse gold particle size, texture and minerals associated with gold (nearly all gold is free and occurs with silicates but not with sulphides) and high gold fineness pointing to a pre-peak metamorphic timing, which are uncommon for orogenic gold deposits (Eilu 2007).

Weighting of the training sites, as was performed in Paper VI, enables the use of deposit size to bias the model towards the greater deposit sizes. Thus, the minor mineral occurrences, which are the most abundant types in the deposit database, do not excessively influence the development of the model (Hronskey & Groves 2008). This weighting approach is more realistic than treating the different training sites as equally important.

Another difficulty with the training sites is the shape of the target deposit type modelled. The orogenic gold deposits are typically elongated, thin and long, and thus are not well represented as individual points, but rather as a series of points along strike as was done in Papers I, II, III and VI. Correspondingly, Poli & Sterlacchini (2007) generated points within the target patterns (landslides). They tested two sets of points in two different spatial resolutions with the assumption that a single point represents a target in their study. They concluded that a single point does not give satisfactory results due to the uncertainty related to the location of each of the points used.

A further consideration is to select an appropriate cell size for the evidence data used for modelling. The cell size has to take into account the deposit dimensions and the spatial resolution of the data as was done in all papers included in this thesis.

The validation methods used in this thesis were both statistical and empirical. The latter, namely field testing and sampling, is still going on after completion of this project. The first results of these field tests were published in Paper V, and the final results were published by Sarala et al. (2007), who demonstrate anomalous gold values in several target areas using till geochemistry and heavy mineral sampling. The statistical tests used were based on either the training sites or the validation sites that were not used for training. Random selection of both validation and training sites was performed so as to avoid bias in modelling. Various jack-knifing techniques also provide solutions for validation, but can be tedious to complete as was the one used in this thesis. However, statistical cross validation of some sort is critical to evaluate the performance of a prediction model or a prospectivity map (Chung & Fabbri 2003, Harris & Sanborn-Barrie 2006, Stensgaard 2006).

This study shows that the prospectivity models can be improved to benefit mineral exploration by adding information about the geological processes needed to form a mineral deposit, following a conceptual mineral system approach. These conceptual evidence layers represent the source, migration and depositional processes in the mineral system being modelled (Hronskey & Groves 2008). A geological map is considered a model in and of itself and the various derivatives of a geological map are used as evidence layers representing proxies for these key parameters of the processes forming a variety of mineral deposits. Another important issue in mineral exploration is the economic factor, which was taken into account by weighting the training sites by the in-situ gold content of a deposit used for training. This is, however, a simplified approach, knowing, as we do, that any mineral deposit is an artefact of the economics of its time. The value of a deposit is dependent on several factors, including metal prices, new extraction technologies, company strategies, etc. Thus a lower probability area can also be important if/when these factors change. Kreuzer et al. (2007) introduce a decision tree technique for quantitative risk analysis and decision-making in mineral exploration. Because it also takes into account the variable economic factors, this is technique that could provide new insights into mineral prospectivity modelling.
4 CONCLUSIONS

The main conclusions of this thesis are:

1. High-resolution airborne geophysics together with regional till geochemistry provide reliable empirical evidence data for reconnaissance-scale first-stage mineral prospectivity mapping for orogenic gold deposits.

2. The predictive power of airborne geophysical data decreases with decreasing spatial resolution, thus suggesting that for small targets, like orogenic gold deposits, high-resolution, less than 200 m line spacing, airborne geophysics, is desirable.

3. The predictive power of an empirical model using geophysical and geochemical data can be enhanced by adding conceptual evidence layers derived from geological maps.

4. An expert defined exploration model can be effectively documented, tested and qualified by using a conceptual-fuzzy logic modelling technique.

5. Field validations have indicated that exploration targets can be generated by quantitatively analyzing spatially referenced data from various sources and that these targets can be ranked based on their exploration potential. This way the exploration area and eventually the costs can be potentially reduced significantly.

6. Various statistical validation techniques, like ROC curves, efficiency curves, cross validation or jackknifing, are needed to evaluate the performance of prospectivity models prior to field evaluation.

7. The advantage of the neural network technique over the other methods used in this thesis is the possibility of using weighting on the training sites based on the size of the deposits.
This study has been financed by the Geological Survey of Finland (GTK) and was part of two research & development projects at GTK from 2002 to 2007. The Centre for International Mobility (CIMO) together with GTK provided financial support for my visit to U.S. Geological Survey in 2003. This visit was the first major milestone in the course of this project, confirming my desire to focus on spatial modelling and prospectivity mapping. The management of GTK has supported my endeavours from the very beginning. I want to thank former regional director Prof. Ahti Silvennoinen and division manager Dr. Erkki Vanhanen for their help in getting the project started. To them and their successors, Mr. Risto Pietilä and Dr. Esko Korkiakoski, as well as to research director Dr. Pekka Nurmi, I am grateful, not only for enabling the resources needed for the project, but for giving me encouraging support in the background. I also owe a great debt of gratitude to Mr. Nils Gustavsson, who gave me valuable advice at the early stages of the project and has always offered me guidance when needed.

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This thesis comprises a synopsis and six original papers dealing with mineral prospectivity mapping of gold within the Northern Fennoscandian Shield, Finland. Geographical information systems (GIS) with weights-of-evidence, logistic regression, fuzzy logic and neural network models were used in these papers to complete a series of spatial modelling tasks to assess the gold potential of Northern Finland. These results can be used to define regional scale target areas for gold exploration.