Mineral prospectivity mapping of lithium-spodumene pegmatites in the Kaustinen region of Finland: Implications for lithium exploration in Finland

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**Title of report**

Mineral prospectivity mapping of lithium- spodumene pegmatites in the Kaustinen region of Finland: Implications for lithium exploration in Finland.

**Abstract**

This report describes analysis and prospectivity mapping of lithium-bearing spodumene pegmatites in the Kaustinen area of Finland using regional-till geochemical and LiDAR-based glacial geomorphological data. The Li-pegmatite pathfinder elements selected for spatial data analysis from the regional-till geochemical data were As, Be, Bi, K, Li, Sb and Zr. Based on an interpreted NNW-SSE trend of glacial transportation, the till geochemical samples were spatially shifted 2km up-ice direction to position the geochemical anomalies over the subsurface bedrock or soil horizon sources. Three prospectivity methods were implemented for mapping the potential of Li-enrichment in the study area. The results from the weights-of-evidence and the logistic regression models show high capture efficiencies, with the area under curve values of 0.909 and 0.917 respectively. The fuzzy model however has relatively low area under curve value, i.e., 0.708. The results from this study can be used to locate areas for detailed ground exploration activities and identification of new Li-rich pegmatites in the Kaustinen area.

**Keywords**

Lithium, exploration, till geochemistry, data analysis, prospectivity mapping, critical metals

**Geographical area**

Kaustinen, Ostrobothnia, Western Finland

**Other information**

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1 INTRODUCTION

To facilitate transition towards a low-carbon economy, the European Commission has created a list of critical raw materials (European Commission 2020) comprising metals and minerals needed for the development of green-technological products. This list includes, for example, metals and minerals used in battery production such as lithium, cobalt and graphite. The global demand for these metals and the source minerals has been increasing rapidly. Hence there is an urgent need for ensuring sustainable supply of these critical raw materials that are needed for development of technologically advanced, low-carbon-emission battery products. Lithium particularly is one of the most important battery metals because of the extensive use of lithium-ion batteries in modern technology. Hence, for the first time in 2020, lithium was added to European Commission’s list of critical raw materials (European Commission 2020).

Mineral exploration and resources assessments activities targeting lithium are being actively pursued across the European Union (EU). Several projects have reached advanced stages of development in Austria, Finland, Portugal, Germany and Spain. Based on the recent progress of exploration and mine development projects in the EU, EL Latunussa et al. (2020) summarizes EU’s lithium resources and reserves. EU’s domestic production of lithium concentrate (of about 110 tonnes of lithium content) and processed lithium compounds is negligible compared to global production (EL Latunussa et al. 2020). EU, therefore, has 100% reliance on imports for its lithium requirements. Lithium is currently imported from Chile (78%), United States (8%) and Russia (4%) (European Commission, 2020). For sustainable development and stability of a green economy, it is imperative that the reliance of EU on imports of metals and minerals that are of economic and strategic significance should be reduced. Assessments of national level mineral resources of the critical battery minerals such as lithium-bearing spodumene are therefore crucial. The national and international collaborations within the EU also emphasize on exploration of mineral resources within the EU for ensuring strategic independence with respect to sourcing, acquisition and self-production of these critical raw materials and thereby securing their availability to meet EU’s current and future industry and production requirements.

Finland is one of the few EU countries with high potential for lithium mineral resources. The main source of lithium is the spodumene mineral in LCT (Li, Cs, Ta) pegmatites. In Finland such pegmatites occur in southern Ostrobotnia around Kaustinen, Somero-Tammela, Kitee-Tohmajärvi, Haapaluoma-Kaatiala, Eräjärvi, Seinäjoki, Heinola, Kisko, Kemiö and Kalajoki (Alviola 2012). Of these the Somero-Tammela and Kaustinen areas are important lithium provinces and have been the main focus of exploration activities in the recent years (Sarapää et al. 2015). In the Somero-Tammela lithium province the deposits contain high-quality petalite and spodumene in economic concentrations within the albite-petalite-spodumene pegmatites (Sarapää et al. 2015). The Kaustinen lithium province contains several albite-spodumene pegmatite deposits such as at Länttä, Emmes, Outovesi, Suvajärvi, Leviäkangsas and Rapasaaret, for which mineral resources estimates have also been calculated.
The GIS-based lithium potential assessment for the Somero-Tammela area was implemented by Leväniemi (2013). However, a systematic GIS-based mineral prospectivity analysis does not exist for the Kaustinen area. The assessment of possible new raw material resources in different regions requires not only good geological background but also new methodological approach to identify unknown, subsoil occurrences. For identifying most potential areas for the critical minerals and metals, there are modern data analysis techniques which combine different geological, geochemical and geophysical mapping data and analytical datasets. Integration of the datasets help in estimating suitable source areas or lithological structures for detailed mineral exploration in the areas of transported cover or deeper ore bodies. In this approach, spatial analysis and statistical approach with data integration techniques (for e.g., self-organizing maps with 3D visualization, prospectivity modelling and GIS-based modelling tools) can be used. Hence this study focuses on data analysis and regional scale prospectivity mapping for lithium potential in the Kaustinen area using different geostatistical methods. Furthermore, in the glaciated terrains different landforms can provide an overview to glacial transportation directions which is important for tracing the source areas of geochemical anomalies in till data. In the areas of thick glacial sediment cover and multiple glaciation phases with complex till stratigraphy as well as in challenging ore types or deep ore bodies in poorly known lithological environment, new and advanced data analysis techniques are needed in detection of potential source areas for mineralization.

Hence the aim of the task presented in this study was to implement data mining and spatial data analysing techniques for regional potential of undiscovered lithium resources in the Central Ostrobothnia area (focusing on the Kaustinen and its surrounding areas). This is crucial because the spodumene pegmatites have low geophysical signature and challenging glacial overburden conditions with a low number of bedrock outcrops. Spatial analyses included geostatistical data processing and prospectivity modelling using geological, geochemical and geophysical datasets, integrated with estimated glacial transport directions and distances based on regional geomorphological interpretation (LiDAR DEM) models.

2 STUDY AREA

The study area is located in the Ostrobothnia area surrounding the Kaustinen region in western Finland (Figure 1). The bedrock is composed of the Proterozoic paragneisses, volcanic rocks and black schists of the Pohjanmaa belt surrounded by the granitic rocks belonging to the Central Finland Granitoid Complex (Korsman & Koistinen 1998, Vaasjoki et al. 2005). The Pohjanmaa belt hosts several rare element pegmatites (Alviola et al. 2001), and the Li pegmatites of the Kaustinen province belong to the albite-spodumene type. Pegmatites crosscut the metavolcanic and metasedimentary rocks at the northern edge of the belt. At least 16 separate pegmatite occurrences are known in the area mainly focusing on the Kaustinen region (Ahtola et al. 2015). Bedrock of the Kaustinen area is covered by Quaternary sediments, particularly glacial till which has been deposited during two main ice flow phases: the first (older) from WNW and the second (younger) from NW (Figure 2). The first phase is seen as drumlin field with some megaflutings.
oriented along the WNW-ESE ice flow. The second phase is characterized by the drumlin field including smaller features than the older one. In the eastern part small areas can be identified as transversal moraine ridge topography (ribbed moraines) overlying the older drumlin topography (Sarala 2020). Spodumene pegmatite boulders are the only visible evidence of the lithium pegmatites in the field. Due to the lack of outcrops, diamond drilling was the most useful method for sampling spodumene pegmatites in the Kaustinen district that led to discovery of four new spodumene pegmatites in the area (Ahtola et al. 2015).

Figure 1: (a) Regional geological map of the study area with an overlay of known deposits and occurrences in the Kaustinen region. These are labelled as Sy: Syväjärvi, Ra: Rapasaaret, Pä: Päivänevä, He: Heikinkangas, Le: Leviäkangas, Ma: Matoneva, Ou: Outovesi, Em: Emmes and Lä: Länttä (b) Sampling locations of 'Targeting till' data in the study area. The samples are graded by the Li-content of the till samples.
3 DATA AND METHODS

3.1 Data

This task was implemented using the Geological Survey of Finland’s (GTK’s) targeting till and bedrock geochemical data (Figure 1b). The targeting till geochemistry data was collected for detailed local geochemical mapping of till in Finland. This dataset is compiled from nationwide collection of soil samples by GTK, sampled along linear transects in 1971–1983. The sampling strategy followed the 1:100 000 map sheets arranged in a discretionary order. Samples included mainly till, but some samples also comprise sorted mineral soils and weathered bedrock and/or a mixture of both (GTK n.d.).

In the Kaustinen area the targeting till dataset comprises about 22,420 data points, sampled every 100 – 400 m along each sampling line; the inter-line spacing ranges between 500 – 2000 m (Gustavsson et al. 1979). This dataset has analytical data for 45 elements (major, minor and trace elements) measured across 14 measurement channels. The dataset ‘Targeting till geochemistry’ and related metadata are available at GTK’s Hakku webportal (hakku.gtk.fi). Additional details of the sampling, analytical methods and geochemical measurements can be found in Gustavsson et al. (1979), Kontoniemi (2011, 2012 and 2013) and Ahtola et al. (2015). For the current study the Li-pegmatite pathfinder elements selected for spatial data analysis were As, Be, Bi, K, Li, Sb and Zr. Other Li-pegmatite pathfinder elements were excluded, because only the above-mentioned elements had uniform coverage over the study area to facilitate spatial interpolations and
subsequent spatial data modelling. The Mineral Deposit Database of Finland identifies eight deposits and occurrences in the Kaustinen area. These are Syväjärvi, Rapasaaret, Päävänne, Heikinkangas, Leviäkangas, Outovesi, Emmes and Länttä (Figure 1). The Li-rich spodumene pegmatites in these deposits and occurrences are not exposed on the surface. However, GTK has conducted bedrock drilling in this area around these deposits (Ahtola et al., 2015). This ‘Bedrock drilling’ data (available from haaku.gtk.fi) was used in this study for generating training points for Li-potential mapping.

3.2 Methods

3.2.1 Data pre-processing

Studies on palaeo-reconstructions of glacial flow dynamics in Finland (Johansson et al. 2011 and Sarala 2020) indicate transportation of glacial till from NNW to SSE for about 1.5 – 2 km. Hence for this study the line-till geochemistry data was corrected for a NNW-SSE directed glacial transportation of till. A spatial shift of 2 km upstream the interpreted glacial transportation direction was applied to the sample points to position them over the subsurface bedrock/soil horizon sources.

In the next step the data was centred-log ratio (clr) transformed (Aitchison 1982, 1986) to identify the geochemical anomalies in the selected pathfinder elements (As, Be, Bi, K, Li, Sb and Zr). The clr transformation can be mathematically expressed as given in Eq. 1 below:

\[
clr(x) = \log \frac{x_i}{\sqrt{x_1 \times x_2 \ldots x_D}}
\]

where, \(x\) is the value of feature vector for \(i = 1, 2, \ldots, D\). The quantity \(\frac{1}{\sqrt{x_1 \times x_2 \ldots x_D}}\) represents the geometric mean of composition with components D.

For each element, the data was first normalized and then the clr transformation was applied. This approach (i) corrects the (commonly) right-skewed geochemical data to a near-normal distribution, (ii) normalizes the geochemical anomalies with respect to the geometric mean and (iii) consequently facilitates enhancement of geochemical anomalies of the selected pathfinder elements. Data normalization also enables reduction of levelling issues related to bias in sampling along the boundaries of different map sheets. Next the clr-transformed data was used to create interpolated rasters for the entire study area. The inverse distance weighted (IDW) interpolation technique was used. Unit cell size for interpolation was 200x200 m². The interpolated rasters (Figures 3-6) were finally used as input predictor maps for fuzzy logic, weights-of-evidence and logistic regression based regional scale lithium-pegmatites prospectivity modelling. The fuzzy logic method was implemented on the continuous numeric rasters. The weights-of-evidence and logistic regression calculations cannot be performed on continuous-numeric datasets. Hence for these methods, the interpolated data was discretized using the z-score-based classification scheme. Figure 7 summarizes the data processing and modelling workflow.
Figure 3: Till geochemistry - Centred log-ratio (clr) transformed data for As in till samples. For labelling of the deposits and occurrences refer to the caption of Figure 1.
Figure 4: Till geochemistry - Centred log-ratio (clr) transformed data for (a) Be and (b) Bi in till samples. For labelling of the deposits and occurrences refer to the caption of Figure 1.
Figure 5: Till geochemistry - Centred log-ratio (clr) transformed data for (a) K and (b) Li in till samples. For labelling of the deposits and occurrences refer to the caption of Figure 1.
Figure 6: Till geochemistry - Centred log-ratio (clr) transformed data for (a) Sb and (b) Zr in till samples. For labelling of the deposits and occurrences refer to the caption of Figure 1.
3.2.2 Modelling methods

GIS-based prospectivity mapping was implemented using the interpolated rasters of clr-transformed data. Three prospectivity methods, viz., fuzzy logic, weights-of-evidence (WofE) and logistic regression (LR) were used. The multi-method modelling approach was implemented to account for subjective and statistical biases induced in each model because of inherent modelling assumptions. The results can hence complement each other and facilitate comparative analysis of exploration targets.

3.2.2.1 Fuzzy logic

Fuzzy-logic overlay is a knowledge-driven method based on the theory of fuzzy sets (Zadeh 1973). A fuzzy set is the extension of a classical set such that the degree of membership to fuzzy sets grades from 0 to 1 (Zadeh 1973). A fuzzy set, hence, allows for a simplified representation of real-world phenomena including geological processes. Fuzzy transformation is the most important step of fuzzy logic method. This step does not require training data, and the model parameters for fuzzy transformations can be assigned based on geological knowledge of the mineral system or based on the anomalies identified from the statistical distribution of the input variables.
more than one fuzzy set are identified in a dataset and combined using logical operators, it forms a fuzzy-logic overlay.

In this study we used the statistical approach to apply fuzzy transformations and identify the anomalous values. Because the data pre-processing steps created normally distributed data, values that were one standard deviation above the mean were used as a threshold for identification of geochemical anomalies. Accordingly using the half-normal (left-sided) Gaussian membership function these threshold values attained the fuzzy membership value of 0.5 after transformation. The membership value increases progressively along the fuzzy membership curve as the input values increase from the threshold value. Table 1 gives the data statistics and the parameters of the fuzzy transformation functions. Finally, the fuzzified rasters were integrated using a gamma operator to derive the fuzzy logic based prospectivity map (Figure 8a).

### Table 1: Data statistics and parameters of fuzzy transformation functions for fuzzy logic-based method

<table>
<thead>
<tr>
<th>Elements</th>
<th>Data Statistics</th>
<th>Fuzzy Transformation Function Parameters*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Minimum</td>
<td>Maximum</td>
</tr>
<tr>
<td>As</td>
<td>-0.7061</td>
<td>1.3872</td>
</tr>
<tr>
<td>Be</td>
<td>0.0000</td>
<td>0.8915</td>
</tr>
<tr>
<td>Bi</td>
<td>-1.1887</td>
<td>2.2056</td>
</tr>
<tr>
<td>K</td>
<td>-1.1460</td>
<td>1.3987</td>
</tr>
<tr>
<td>Li</td>
<td>-1.5944</td>
<td>1.8051</td>
</tr>
<tr>
<td>Sb</td>
<td>-1.6154</td>
<td>1.1580</td>
</tr>
<tr>
<td>Zr</td>
<td>-0.7885</td>
<td>0.5545</td>
</tr>
</tbody>
</table>

*Transformations using half-normal (left-sided) Gaussian function given below:

\[
\mu(x) = \frac{1}{1 + \left(\frac{x}{\mu}\right)^2} - \sigma
\]

### 3.2.2.2 Weights-of-evidence

The weights-of-evidence is a data-driven method for quantification of spatial associations between the input predictor maps (i.e., the evidential layers) and the targeted mineral deposit. The locations of known deposits and occurrences are used as ‘training’ points for the statistical quantifications. The Bayes’ Theorem (Eq. 2) forms the core of the weights-of-evidence approach. On application of Bayes’ theorem to mineral prospectivity mapping, the Bayes’ equation can be used to predict the probability of the occurrence of the targeted mineral deposit (D) given the ‘evidential events’, (E). These evidential events are the datasets representing geological features such as lithology, structures, whole rock geochemistry etc. The occurrence of a mineral deposit can be associated with either the presence or the absence of an evidential event such that posterior probability of occurrence of the targeted deposit D, given an evidential event E, can be...
estimated from the prior belief (the unconditional probability) of the deposit combined with the likelihood (conditional probability) and the marginal probability of the evidential event. (Eq. 2).

\[
P(D|E) = \frac{P(D)P(E|D)}{P(E)} \tag{2}
\]

where, \( P(D|E) \) = Posterior probability of the presence of deposit \( D \), given the presence of the evidential event \( E \),
\( P(D) \) = Prior belief or prior (unconditional) probability of the presence of deposit \( D \),
\( P(E|D) \) = Likelihood (conditional probability) of the evidential event \( E \) given the presence of the deposit \( D \), and
\( P(E) \) = Marginal probability of the evidential event \( E \).

For multiple evidential features, i.e., predictor maps \( E_1 - E_n \), the Bayes’ equation can be used to calculate the updated posterior probability of presence of the deposit given the presence of the evidential events \( E_1 \) to \( E_n \) as presented in Eq. 3 under the assumption that the evidential events are conditionally independent.

\[
P(D|E_1, E_2, \ldots, E_n) = \frac{e^{\log P(D|E_1, E_2, \ldots, E_n)}}{1 + e^{\log P(D|E_1, E_2, \ldots, E_n)}} \tag{3}
\]

The weights-of-evidence method works on an important assumption that the datasets are conditionally independent. Hence the Agterberg-Cheng test of conditional independence (Agterberg & Cheng, 2002) should be used to test the datasets and results for conditional independence (see section 3.2.2.4).

The mathematical implementation of the weights-of-evidence method broadly involves two steps (Bonham-Carter et al., 1988; Agterberg et al. 1990):

i. Quantification of the spatial association (i.e., weights) between the deposit and the evidential events.

ii. Updating the posterior probabilities of the presence of deposit/occurrence by combining the weights-of-evidences of all the evidential events.

The net strength of spatial association between the deposit and an evidential event can be measured using the ‘Contrast’, \( C \) between the positive and the negative weights (\( W^+ \) and \( W^- \) respectively). The contrast value is the difference between the positive weights and the negative weights. A high positive contrast implies strong positive spatial association (\( W^+ \gg \gg W^- \)), while a high negative contrast implies strong negative spatial association (\( W^+ \ll \ll W^- \)). At contrast value 0, there would exist no spatial association between the deposit and the evidential event.

In this study, the spatial associations between the geochemical anomalies and known mineral deposits and occurrences were quantified from calculations of the cumulative descending weights of clr-transformed data (Table 2). These were then integrated according to Eq. 3 to create the prospectivity map from the data-driven weights-of-evidence method (Figure 8b).
Table 2: Quantification of spatial association using the weights-of-evidence method

<table>
<thead>
<tr>
<th>Element</th>
<th>Contrast</th>
<th>Studentized Contrast</th>
<th>Generalized W*</th>
<th>W* STD</th>
</tr>
</thead>
<tbody>
<tr>
<td>As</td>
<td>4.0229</td>
<td>3.938</td>
<td>1.1896</td>
<td>0.2087</td>
</tr>
<tr>
<td>Be</td>
<td>1.4374</td>
<td>3.5072</td>
<td>1.0074</td>
<td>0.3017</td>
</tr>
<tr>
<td>Bi</td>
<td>0.6389</td>
<td>1.4223</td>
<td>0.2318</td>
<td>0.2426</td>
</tr>
<tr>
<td>K</td>
<td>0.5694</td>
<td>1.2676</td>
<td>0.2019</td>
<td>0.2426</td>
</tr>
<tr>
<td>Li</td>
<td>0.7413</td>
<td>1.5722</td>
<td>0.2427</td>
<td>0.2358</td>
</tr>
<tr>
<td>Sb</td>
<td>2.157</td>
<td>2.1014</td>
<td>0.2741</td>
<td>0.2085</td>
</tr>
<tr>
<td>Zr</td>
<td>2.4195</td>
<td>3.9196</td>
<td>0.8242</td>
<td>0.2183</td>
</tr>
</tbody>
</table>

(i) Contrast divided by Standard deviation of contrast; (ii) Generalized positive weights; (iii) Standard deviation of generalized positive weights

3.2.2.3 Logistic regression

As opposed to the Weights-of-evidence method, which is a (log)-linear model, logistic regression is a non-linear approach that fits a logistic (sigmoid) function to the data to calculate the probability of finding a deposit for the given evidential layers. Mathematically, it can be expressed as follows (Porwal et al., 2010):

\[
\pi(d) = \frac{e^{\alpha + \beta_i x_i}}{1 + e^{\alpha + \beta_i x_i}}
\]

where \( \pi(d) \) is the probability of occurrence of a deposit, \( x_i \) is the \( i \)-th \((i=1 \text{ to } N)\) predictor map, \( \alpha \) is a constant, and \( \beta_i \) is the regression coefficient for \( x_i \). Calculation of the regression coefficients follows the maximum likelihood method (Cox & Snell 1989). These coefficients are indicative of relative importance of the input predictor maps. If for a predictor map \( x_i \), the logistic regression co-efficient \( \beta_i = 0 \), then \( x_i \) is a neutral indicator of the targeted deposit. However, if \( \beta_i > 0 \), then \( x_i \) is a positive indicator of the targeted deposits and if \( \beta_i < 0 \), then \( x_i \) is a negative indicator of the targeted deposits. This method does not require the input predictor maps to be conditionally independent and therefore is implemented in conjunction with the weights-of-evidence method, when conditional independence of input variables is not achievable (Agterberg, 1992a, b, Agterberg et al. 1993, Carranza & Hale 2003, Nykänen & Salmirinne 2007 and Nykänen et al. 2008). In the current study, inputs to the logistic regression model were the same as that of the weights-of-evidence model. The logistic regression coefficients are tabulated in Table 3.

Table 3: Logistic Regression (LR) coefficients

<table>
<thead>
<tr>
<th>Element</th>
<th>LR Coefficient</th>
<th>LR Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>As</td>
<td>2.6747</td>
<td>1.0390</td>
</tr>
<tr>
<td>Be</td>
<td>1.6467</td>
<td>0.4877</td>
</tr>
<tr>
<td>Bi</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>K</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Li</td>
<td>8.4079</td>
<td>14.6087</td>
</tr>
<tr>
<td>Sb</td>
<td>1.4857</td>
<td>0.6350</td>
</tr>
<tr>
<td>Zr</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>LR -Constant: -33.6039; standard deviation: 29.3009</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 8: Li-pegmatite potential maps for the study area in the Kaustinen region from (a) Fuzzy logic method, (b) weights-of-evidence method, and (c) Logistic regression method. For labelling of the deposits and occurrences refer to caption of Figure 1.
3.2.2.4 Conditional independence

The weights-of-evidence method is a (log)-linear model, consequently the posterior probabilities in the results are over amplified if the assumption of conditional independence of input evidential layers is violated. Logistic regression on the other hand remains unaffected by linear correlation and conditional dependence of the input datasets. We tested both the models for conditional independence using the tests of conditional independence proposed by Bonham-Carter (1994) and Agterberg & Cheng (2002). The overall CI (Conditional Independence) test of Bonham-Carter (1994) compares the number of observed training points to the expected number of targeted deposits (the expected number is derived from the sum of the posterior probabilities for all unit cells in the study area, Bonham-Carter 1994, Kemp et al. 1999 and Agterberg & Cheng 2002). An overall CI value greater than 15% indicates conditional dependence. Values between 10 – 15% could be indicative of acceptable conditional dependence. The Agterberg-Cheng test of CI is a one-tailed test for the null hypothesis that the expected value of the sum of all posterior probabilities is equal to total number of discrete event if all map layers are conditionally independent (Agterberg & Cheng 2002). Rejection of the null hypothesis implies existence of conditional dependence between the input layers.

The weights-of-evidence and logistic models were tested for conditional independence using the overall CI test (Bonham-Carter 1994) and the Agterberg – Cheng test of CI (Agterberg & Cheng 2002). The result of the tests for the weights-of-evidence model yielded the overall CI of 10.9 % and the Agterberg-Cheng CI probability value of 94 %. Results with CI < 95 % for the Agterberg-Cheng test indicate presence of some conditional dependencies, but these results fall within the range of acceptance (Agterberg & Cheng, 2002). For the logistic regression model the overall CI value is 0.2% and the probability that the model is not conditionally independent is 0.1%. This indicates that the logistic regression model is insensitive to the conditional independence assumptions. The logistic regression coefficients indicate that Bi, Li and K are neutral indicators of Li-bearing pegmatites for the current datasets and the study area. As, Be, Sb and Zr are all positive indicators, but As and Sb are the stronger ones.

4 RESULTS AND CONCLUSION

Three prospectivity maps were created for mapping the potential of Li-enriched pegmatite in the Kaustinen area (Figure 8). These maps capture the well-explored central region as highly prospective. To facilitate comparative and collective evaluation of the results from all the three models, a combined prospectivity map (Figure 9) was generated by rank-based overlay of all the three prospectivity maps. The weights-of-evidence and the logistic regression models show high capture efficiencies, with the area under curve values of 0.909 and 0.917 respectively (Figure 10). The fuzzy model has relatively low area under curve value, i.e., 0.708. The combined prospectivity map in Figure 9 also shows high capture efficiency with area under curve value of 0.891 (Figure 10).

The Kaustinen area in Finland is a well-known Li-province. There occurs a cluster of prospects (deposits and occurrences) in the central part of the study area. This cluster is comprised of
Syväjärvi, Rapasaaret, Päivänevä, Heikinkangas, Leviäkangas, Outovesi and Emmes prospects (Figure 1). All the prospectivity maps identify the central part hosting this cluster as high potential area (Figures 8 and 9). Keliber Technology Oy is involved in exploration drilling in the area of the known deposits and occurrences. The results from this study additionally identify the unrecognized potential of lithium pegmatites outside the main central-exploration area. Figure 8 shows the general zones for future exploration, while Figure 9 presents more localized target areas based on collective assessment of all the three prospectivity maps. The results from this study can hence be used to locate areas for detailed ground exploration activities and identification of new Li-rich pegmatites in the Kaustinen area.

Bedrock exposures are sparse in the Kaustinen region, and the only indication of lithium pegmatites are glacially transported boulder fans down-ice (to the southeast) of all of the discovered occurrences (Sarapää et al. 2015; see also Ahtola et al. 2015). However, this study demonstrates that geochemical anomalies in till samples can be useful indicators of lithium spodumene pegmatites after spatial correction of the sampling locations in the interpreted up-ice direction. This can be seen in Figures 5 – 6, where anomalies in pathfinder elements such as K, Li, Sb and Zr are located around the known deposits and occurrences. Ahtola et al. (2015) used lithium anomalies in till data and boulder fans to identify the presence of lithium pegmatites in the Kaustinen area, followed by diamond drilling and whole rock geochemical analysis. Their study discovered four new spodumene pegmatites viz., Matoneva, Päiväneva, Heikinkangas and Rapasaaret. The current study was built up from the study by Ahtola et al. (2015) for detailed GIS-based regional-scale spatial data analysis of geochemical anomalies in till geochemistry to identify other lithium-spodumene pegmatites in the study area. However, in this study selection of pathfinder elements was based on previous studies and literature review. Hence, for future work, advanced machine learning methods such as principal component analysis, self-organizing maps and artificial neural networks are recommended for identifications of the elemental sub compositions representative of spatial proxies to lithium-spodumene pegmatites in till geochemistry data.
Figure 9: Final Li-pegmatite potential map for the study area in the Kaustinen region. For labelling of the deposits and occurrences refer to the caption of Figure 1.
Figure 10: Efficiency assessments of the prospectivity mapping results.

5 REFERENCES


