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1 **A machine learning approach to tungsten prospectivity modelling using** 2 **knowledge-driven feature extraction and model confidence**

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11 *Keywords*

12 Machine learning; Mineral prospectivity modelling; Mineral exploration; Random Forest™; Tungsten;
13 SW England

14

15 **Abstract**

16 Novel mineral prospectivity modelling presented here applies knowledge-driven feature extraction to a
17 data-driven machine learning approach for tungsten mineralisation. The method emphasises the
18 importance of appropriate model evaluation and develops a new Confidence Metric to generate
19 spatially refined and robust exploration targets. The data-driven Random Forest™ algorithm is
20 employed to model tungsten mineralisation in SW England using a range of geological, geochemical
21 and geophysical evidence layers which include a depth to granite evidence layer. Two models are
22 presented, one using standardised input variables and a second that implements fuzzy set theory as
23 part of an augmented feature extraction step. The use of fuzzy data transformations mean feature
24 extraction can incorporate some user-knowledge about the mineralisation into the model. The
25 commonly subjective approach is guided using the Receiver Operating Characteristics (ROC) curve
26 tool where transformed data are compared to known training samples. The modelling is conducted
27 using 34 known true positive samples with 10 random sets of randomly generated true negative
28 samples to test the random effect on the model. The two models have similar accuracy but show
29 different spatial distributions when identifying highly prospective targets. Areal analysis shows that the
30 fuzzy-transformed model is a better discriminator and highlights three areas of high prospectivity that
31 are not previously known. The Confidence Metric, derived from model variance, is employed to further
32 evaluate the models. The new metric is useful for refining exploration targets and highlighting the
33 most robust areas for follow-up investigation. The fuzzy-transformed model is shown to contain larger
34 areas of high model confidence compared to the model using standardised variables. Finally, legacy
35 mining data, from drilling reports and old mine descriptions, is used to further validate the fuzzy-

36 transformed model and gauge the depth of potential deposits. Descriptions of mineralisation
37 corroborate that the targets generated in these models could be undercover at depths of less than
38 300 m. In summary, the modelling workflow presented herein provides a novel integration of
39 knowledge-driven feature extraction with data-driven machine learning modelling, while the newly
40 derived Confidence Metric generates reliable mineral exploration targets.

41

42 1. Introduction

43 The use of Machine Learning Algorithms (MLAs) for mineral prospectivity modelling has
44 been driven by the increasing size of individual datasets and the range of data types
45 available for mineral exploration. MLAs are computationally efficient and can deal with
46 large, high-dimensional input datasets, non-Gaussian distributions, and generate robust
47 exploration targets from few training samples (Emmanuel John M. Carranza and Laborte,
48 2015a, 2015b; Rodriguez-Galiano et al., 2015). The approach requires some *a priori* data to
49 train the model indicating it is a data-driven method. However, the number of training
50 samples can be <20 which is a significant improvement compared to other data-driven
51 methods such as Weights-of-Evidence (Emmanuel John M. Carranza and Laborte, 2015b).
52 MLAs are now commonplace in mineral prospectivity modelling. The Random Forest,
53 Support Vector Machine and Artificial Neural Network algorithms are regularly
54 implemented and it is the Random Forest MLA that is proving most effective in comparison
55 studies (Rodriguez-Galiano et al., 2015; Sun et al., 2019).

56 Prospectivity modelling is often conducted at a large-scale, encompassing national or
57 regional areas to determine new exploration targets. Studies have become increasingly
58 effective due to investment in the acquisition of high-resolution airborne geophysical,
59 satellite and geochemical datasets over large areas (Bahiru and Woldai, 2016; Kreuzer et al.,
60 2010). Furthermore, the commitment from state geological surveys to undertake airborne
61 geophysical surveys and geochemical baseline studies for both mineral exploration and
62 environmental purposes has led to high-quality datasets often being freely available.

63 Classical prospectivity modelling has been dominated by the Weights-of-Evidence and Fuzzy
64 Logic methods. Whilst MLAs may be a more effective data-driven method, the Fuzzy Logic
65 technique is knowledge-based and founded on fuzzy set theory. The approach allows user-
66 knowledge to be incorporated into the model through various data transformations chosen
67 by the user (An et al., 1991; Bonham-Carter, 1994; Zadeh, 1965). The advantage of this is
68 the ability to weight different data and to introduce some dependencies between variables
69 that may be inferred by the user but not captured in the data. Until recently, this technique
70 has been considered highly subjective but work by Nykänen et al. (2015, 2017) provides a
71 means of guiding the data processing. By using fuzzy transformations as part of the feature
72 extraction step in MLA modelling, some user-knowledge can be introduced to potentially
73 improve a data-driven analysis.

74 MLAs also offer key post-hoc metrics to evaluate the model beyond the standard accuracy
75 metrics. These include model variance and information entropy, which have been
76 investigated, respectively, by Cracknell and Reading (2013) and Kuhn et al. (2018). Cracknell

77 and Reading (2013) demonstrated the value of assessing model variance for a multi-class
78 problem when mapping lithology to highlight fault zones, whereas Kuhn et al. (2018) used
79 information entropy to guide field sampling campaigns to assist with geological mapping.
80 These metrics are useful for highlighting potentially erroneous aspects of a model, which
81 cannot be found when evaluating a model through a single accuracy metric, but have not
82 been implemented within a mineral prospectivity modelling framework.

83 Herein, we demonstrate the use of fuzzy set theory for feature extraction, as well as post-
84 hoc metrics, for tungsten mineralisation in SW England using a Random Forest MLA. We
85 explore how incorporating knowledge-driven principles as part of feature extraction within
86 a data-driven modelling workflow can improve the final results and compare this to a model
87 using standardised (zero mean and equal variance) input variables. Furthermore, the models
88 are spatially evaluated using model variance and a newly derived Confidence Metric which
89 are applied to generate robust targets for mineral exploration with a refined area. Finally,
90 legacy mining data are used to further validate new targets and give a depth estimate to
91 mineralisation.

92 1.1. Prospectivity modelling and machine learning

93 MLAs are versatile tools for mineral prospectivity modelling but can be misused if the data
94 preparation and model evaluation are inappropriate. Therefore, data preparation, also
95 known as feature extraction, as well as methods of evaluating models through accuracy
96 statistics and other metrics, are briefly considered below.

97 1.1.1. Feature extraction

98 The advent of high-resolution datasets of various types has meant that mineral prospectivity
99 models often include high numbers of input variables which increase the dimensionality.
100 Minimising the number of variables means redundant data can be reduced to avoid skewing
101 the results, therefore improving classification accuracy and reducing computation times
102 (Witten et al., 2017). The other reason for selecting a minimum number of variables is to
103 mitigate the “curse-of-dimensionality”, also known as the “Hughes effect” (Hughes, 1968)
104 whereby the number of training samples required to capture data variance increases
105 disproportionately with the number of variables. This is an important consideration when
106 only a small number of training samples are available. Feature extraction and careful data
107 processing is of paramount importance to minimise both data redundancy and the number
108 of input variables.

109 The process of manipulating variables to enhance desirable characteristics is known as
110 feature extraction. Commonly, the aim is to highlight a particular range in the original data,
111 through simple statistics or combining with other variables (e.g. multiplication or ratios), to
112 amplify interactions between different variables (Henery, 1994a, 1994b). Some of these
113 options may also have the benefit of mitigating noise and removing correlated data (Hastie
114 et al., 2009). Another option is to highlight particular features using data transformations or
115 image enhancements. There are a broad range of transformations which can be tailored to
116 the task and, when used appropriately with an appropriate MLA, a high degree of accuracy
117 can be achieved (Sukumar et al., 2014).

118 In mineral prospectivity modelling, it is common for initial data preparation to include
119 computing the distance from particular features as an example of feature extraction (e.g.
120 proximity-to structures). Many prospectivity models attempt to use factor analysis, principal
121 component analysis or the singularity method to process data, which are other forms of
122 feature extraction (Abedi et al., 2013; C. Wang et al., 2017; J. Wang et al., 2017; Wang et al.,
123 2018; Zhao et al., 2015). The transformation and weighting of data is also part of the feature
124 extraction process, of which fuzzy membership and fuzzy operators in a Fuzzy Logic
125 approach are an example of feature extraction by transforming the data and weighting
126 desirable features within the study area.

127 1.1.2. Model evaluation

128 The output for mineral prospectivity modelling using MLAs is often a binary classification
129 but it is the class probabilities, the likelihood that a pixel is classified correctly, that are of
130 value when considering prospectivity (Harris et al., 2015). It is good practice to evaluate the
131 accuracy of the prospectivity models, most commonly through the Receiver Operating
132 Characteristics (ROC) curve tool (Agterberg and Bonham-Carter, 2005; Fawcett, 2006;
133 Nykänen, 2008; Robinson and Larkins, 2007) which uses *True Positives* (TP), *True Negatives*
134 (TN), *False Positives* (FP) and *False Negatives* (FN) to determine a range of metrics including
135 *Sensitivity* (Equation 1) and *Specificity* (Equation 2). The ROC curve tool plots *Sensitivity*
136 against $1 - \textit{Specificity}$ and this can be used to calculate the Area-Under-Curve (AUC).

$$137 \textit{Sensitivity} = \frac{TP}{TP+FN} \quad (1)$$

$$138 \textit{Specificity} = \frac{TN}{TN+FP} \quad (2)$$

139 MLAs also have further evaluation metrics which are often overlooked, such as the
140 calculation of model variance from class probabilities that can be subsequently presented
141 spatially as a map (Cracknell and Reading, 2013; Kohavi and Wolpert, 1996). Model variance
142 was implemented as part of lithological mapping by Cracknell and Reading (2013) in the
143 Broken Hill area of New South Wales, Australia where higher variance was an indicator for
144 the presence of fault zones and was termed “the upside of uncertainty”. A further derivative
145 of model variance is information entropy used by Kuhn et al. (2018) for similar purposes and
146 shown to be useful in geological mapping campaigns to target areas for follow-up work that
147 may be poorly understood.

148 There have been limited attempts to apply these tools to mineral prospectivity modelling.
149 There is often a predilection for distilling a model to a single accuracy metric, however, this
150 is not ideal especially with spatial data where some aspects of the model may be well-
151 constrained and other components highly suspect. Model variance can spatially highlight
152 where the model is failing and provide useful information to the user that can feedback to
153 initial feature extraction. By incorporating the spatial distribution of model variance into the
154 evaluation process, the user can enhance the analysis and mitigate the potential limitations
155 of a single accuracy metric.

156 1.2. Geological framework

157 SW England hosts a world-class tin-tungsten province and provides an excellent case study
158 site for prospectivity modelling due to the recent acquisition of high-resolution airborne

159 geophysical and geochemical datasets (Beamish et al., 2014; British Geological Survey,
160 2016). The regional geology (Figure 1) is dominated by low-grade regionally
161 metamorphosed Devonian-Carboniferous successions that were deformed during the
162 Variscan Orogeny; these were subsequently intruded by the Early Permian Cornubian
163 Batholith (Leveridge and Hartley, 2006; Scrivener, 2006; Shail and Leveridge, 2009; Simons
164 et al., 2016). The batholith is closely associated with a tin-tungsten orefield that has also
165 been exploited for copper, zinc, lead, silver, antimony, arsenic, uranium and a number of
166 other subordinate metals (Jackson et al., 1989). Tungsten mineralisation is governed by
167 Variscan and post-Variscan regional tectonic and structural development and the coeval
168 magmatic and magmatic-hydrothermal evolution of the batholith; these are briefly
169 discussed below.

170 1.2.1. Regional tectonics and structural geology

171 The regional structural geological evolution records two episodes of deformation (D1 and
172 D2) relating to Variscan convergence and collision (e.g. Sanderson and Dearman, 1973;
173 Alexander and Shail, 1996; Rattey and Sanderson, 1984). These were associated with the
174 development of NNW-directed thrust faults and NNW-SSE transfer faults within Devonian
175 and Carboniferous successions (Coward and Smallwood, 1984; Dearman, 1970, 1963; Shail
176 and Alexander, 1997).

177 NNW-SSE post-convergence extension (D3) commenced in the latest Carboniferous and
178 brought about reactivation of Variscan thrust faults and the generation of new higher angle
179 extensional faults through much of the Early Permian (Figure 2; Shail and Wilkinson, 1994;
180 Alexander and Shail, 1996, 1995). Subsequent and successive minor ENE-WSW (D4) and
181 NNW-SSE (D5) Permian intraplate shortening events are recognised (Hobson and Sanderson,
182 1983; Rattey and Sanderson, 1984; Shail and Alexander, 1997). The D3-D5 events spanned
183 batholith construction and mineralisation and their brittle expression, as faults and tensile
184 fractures, were essential for the migration of magmatic-hydrothermal fluids and the
185 development of lodes and sheeted veins (Shail and Alexander, 1997; Shail and Wilkinson,
186 1994). Tungsten deposits form in cusped bodies of granite and only extend a short distance
187 into the country rock (Ball et al., 1998; Hosking and Trounson, 1959; Jackson et al., 1989).
188 These deposits are commonly proximal to NW-SE major faults (e.g. Hemerdon, Redmoor,
189 Cligga Head) which may control mineralisation either directly or through subordinate
190 structures.

191 1.2.2. Permian granite batholith

192 Five different granite types have been identified across the region: G1, two-mica granite;
193 G2, muscovite granite; G3, biotite granite; G4, tourmaline granite; G5, topaz granite (Simons
194 et al., 2016). The association between granite type and mineral prospectivity is not well-
195 constrained; granite types close to surface are commonly older than, and unrelated to, the
196 lode mineralisation they host. Nevertheless, tourmaline granites (G4) are common in areas
197 of significant tin mineralisation and have been interpreted as the precursor differentiated
198 magmas that released Sn-bearing magmatic-hydrothermal fluids (e.g. Müller et al., 2006).
199 Topaz granites (G5) host very low-grade disseminated Sn-W-Tb-Nb mineralisation but have
200 been inferred to be the source of substantial tourmalinisation haloes and associated Sn-W
201 mineralisation (Manning and Hill, 1990). There is an association between muscovite granites

202 (G2), typically present as small stocks and interpreted as a differentiation product of G1
203 granites, and W mineralisation (Simons et al., 2017, 2016).

204 1.2.3. Tungsten mineralisation and exploration

205 SW England has a number of tungsten deposits which have been described in detail, such as
206 the Cligga Head (Hall, 1971; Moore and Jackson, 1977) and St Michael's Mount (Dominy et
207 al., 1995) sheeted vein systems and the Hemerdon stockwork (Cameron, 1951; Dines, 1956;
208 Shail et al., 2017); the latter recently operated by Wolf Minerals Ltd (2015-2018). It is
209 important to note that almost all tungsten is hosted in wolframite with only trace amounts
210 of scheelite. Figure 3 shows all known tungsten occurrences that are reported in the BGS
211 GeoIndex (2018) (<https://www.bgs.ac.uk/mineralsuk/data/mineocc.html>). Additional
212 tungsten occurrences are known and described in Dines (1956) but are not readily available
213 in digital form and are instead used for qualitative evaluation.

214 Exploration has been selective and focused around known tungsten deposits. Andrews et al.
215 (1987) conducted soil geochemical studies around the Hemerdon deposit which involved
216 three transects and identified geochemical anomalies although no follow up trenching is
217 known. Geochemical exploration at Redmoor, which made use of an extensive diamond and
218 percussive drilling campaign as well as samples of float (rock fragments in soil), attempted
219 to define an alteration halo (Newall, 1994; Newall and Newall, 1989). The work used factor
220 analysis to identify a "mineralisation factor" for the elements As, Cu, W, Sn, Na* and Zr
221 (where * indicates a negative correlation). Beer et al. (1986) identify clear geochemical
222 anomalies for tungsten, based on percussive drilling along traverses, nearby to the Castle-
223 an-Dinas tungsten lode. The Mulberry and Wheal Prosper area was investigated by Bennett
224 et al. (1981) who found both tungsten and tin anomalies in proximity to calc-silicate units in
225 the Meadfoot Group in soil geochemistry. Regional investigations were undertaken by
226 Moore and Camm (1982) and James and Moore (1985) using space-borne Landsat MSS and
227 Seasat data to map regional structures associated with tungsten mineralisation.

228 2. Data and Methods

229 The workflow illustrated in Figure 4 shows the steps required to incorporate knowledge-
230 based feature extraction into a data-driven modelling workflow and generate spatially
231 refined robust targets for mineral exploration. These include defining the conceptual
232 deposit model, initial data preparation, feature extraction using fuzzy transformations and
233 machine learning modelling. Models generated through the Random Forest MLA are
234 evaluated through model variance and a Confidence Metric to highlight spatially refined and
235 robust mineral exploration targets.

236

237 2.1. Conceptual tungsten deposit model

238 The conceptual deposit model for the target mineral deposit enables the user to identify key
239 exploration criteria. These are represented by evidence layers, generated from available
240 datasets. Regional geological, geochemical and geophysical datasets have been
241 incorporated in this work to identify tungsten mineralisation in SW England. The
242 contribution of these evidence layers to the conceptual deposit model is described below.

243 Prior mineral exploration and geological investigations provide a substantial body of
244 research on which to build a regional conceptual deposit model for tungsten mineralisation
245 in SW England (Andrews et al., 1987; Ball et al., 2002, 1998; Hall, 1971; Hosking and
246 Trounson, 1959; Jackson et al., 1989; Moore and Camm, 1982; Moore and Jackson, 1977;
247 Newall, 1994; Newall and Newall, 1989; Shail et al., 2017). Based on these observations, a
248 conceptual deposit model has been developed to capture the common characteristics of
249 known tungsten deposits (Figure 5). The model is based on a range of available geological,
250 geochemical and geophysical datasets. Geological data comprises the mapped extent of
251 granite plutons based on British Geological Survey 1:50 000 data and a depth to granite
252 layer determined from the LiDAR Digital Terrain Model (DTM) and the granite surface
253 model, based on regional gravity data, created by Willis-Richards and Jackson (1989).
254 Geochemical datasets include soil and stream-sediment data from the G-BASE survey
255 (British Geological Survey, 2016), Tellus South West airborne geophysical surveys (Beamish
256 et al., 2014; Ferraccioli et al., 2014) and lineament data derived by Yeomans et al. (2019).

257 The evidence layers generated from these datasets have been prepared within the ESRI
258 ArcGIS Desktop software package. These data were resampled to a common extent and
259 resolution based on the airborne geophysical data (40 m pixels) and standardised to zero
260 mean and equal variance; as is usual in many machine learning approaches (Camps-Valls et
261 al., 2007; Cracknell and Reading, 2015, 2014; Hastie et al., 2009). The data preparation steps
262 for each layer are presented in the Supplementary Information (S1).

263 2.1.1. Geological evidence layers

264 The geological exploration criteria defined here are based on the observation that tungsten
265 mineralisation generally occurs, in granites or their host rocks, close to the margins of
266 “cusplate” granite bodies or cupolas, at the roof of the batholith (Ball et al., 1998; Beer et al.,
267 1975; Dominy et al., 1995; Hosking and Trounson, 1959). An evidence layer for proximity-to
268 granite was prepared using the British Geological Survey 1:50 000 shapefile data to capture
269 the XY locations of granite contacts. A proximity-to granite layer was also prepared to
270 capture the depth to the granite contact in areas that may have blind mineralisation. The
271 granite surface from the 3D model created by Willis-Richards and Jackson (1989) is
272 subtracted from the LiDAR DTM and included as a proximity-to layer that captures the
273 distance to granite in Z (depth) to identify shallow granite bodies. Due to some areas of the
274 model protruding above surface, the evidence layer was classified into seven groups to
275 allow down-weighting of the protruding areas.

276 Structural information was also included based on observations by Shail et al. (2017) using
277 regional lineament data derived from the airborne geophysics by Yeomans et al. (2019). A
278 proximity-to structures layer using a Euclidean distance algorithm was prepared based on
279 NW-SE lineaments with lengths > 1200 m. Furthermore, a density map of all NW-SE
280 structures was created to capture areas of high fracturing that may be favourable for
281 mineralisation.

282 2.1.2. Geochemical evidence layers

283 Regional soil and stream-sediment geochemical data from the G-BASE survey (British
284 Geological Survey, 2016) were used to derive geochemical evidence layers. The soil data
285 were collected from between 0 and 0.2 m depth and sieved at 2 mm. Stream-sediment data

286 were analysed using X-ray Fluorescence Spectroscopy with no digestive reagent. Strict
287 Quality Assessment and Quality Control was conducted by the British Geological Survey
288 prior to release through the G-BASE survey; detailed by Wragg et al. (2018).

289 Geochemical evidence layers have been created through an Inverse-Distance Weighting
290 (IDW) algorithm based on preparation steps by Carranza (2010) and are summarised in
291 Table 1. The geochemical data includes both soil and stream-sediment datasets for all
292 evidence layers discussed below excluding the K/(Zr/Eu). This ratio is exclusive to the
293 stream-sediment data due the lack of analysis for rare earth elements during analysis of the
294 soil data. These data are considered in three groups representing mineralisation, aureole
295 and granite geochemistry.

296 For mineralisation geochemistry, information on the target metal, W, is included as well as
297 Sn due to this common association (Cameron, 1951; Dines, 1956; Hall, 1971; Jackson et al.,
298 1989; Moore and Jackson, 1977). The inclusion of As, Bi, Sb, Na*, Rb and Cs (where *
299 indicates a negative correlation) is based on the previous exploration campaigns.

300 As, Bi and Sb are used as indicators for mineralisation where tungsten and tin may not be
301 prevalent. They occur at distance from the deposit (Andrews et al., 1987), therefore, these
302 elements may be a vector element in soil geochemistry for mineralisation at depth (or
303 laterally) where the main tungsten mineralisation is undercover and assuming there has
304 been minimal soil transport. It is worth noting that Sb is considered to not a reliable
305 indicator element by Ball et al. (2002) but is included to determine its importance in this
306 particular study.

307 The inclusion of Na*, Rb and Cs and ratios such as K/Rb* and K/Cs* is based on aureole
308 geochemistry and alteration in mineralised country rocks surrounding granite cupolas (Ball
309 et al., 1998; Newall and Newall, 1989). Other elements that are enriched include Li and F
310 (Andrews et al., 1987; Ball et al., 1998; Newall, 1994; Newall and Newall, 1989), but there
311 are insufficient analyses for these elements across the region and they have therefore not
312 been included.

313 Litho-geochemical evidence layers are focused on granite types and these are defined using
314 two ratios. Ti/Sn* is useful for determining a general granite signature (Ball et al., 1984,
315 1998) but fails to separate specific granite types. By interrogating geochemical data from
316 Simons et al. (2016), an indicator ratio has been found, K/(Zr/Eu), to separate the G2 granite
317 from other granite types (Figure 6); albeit with some close associations with the G1a type.
318 Other useful ratios have been identified such Zr/Fe₂O₃, Nb/Zr and Ba/Rb but are largely
319 indistinct for separating G2 granites (Simons et al., 2016). Potential indicator elements for
320 G2 granite types include Be and Li (Simons et al., 2017); however, these are not included in
321 the available soil and stream-sediment geochemical datasets for the region.

322 2.1.3. Geophysical evidence layers

323 The geophysical evidence layers defined in the conceptual deposit model incorporate
324 airborne radiometric data from the Tellus South West project. The magmatic-hydrothermal
325 aureole around granite plutons in SW England is highlighted by the ratio of $\tan^{-1}(K/eU^*)$. It
326 is therefore included to capture hydrothermal alteration where elevated uranium
327 concentrations indicate that mineralising fluids may have circulated; as with geochemical
328 ratios the evidence layer is an inverse relationship. The inverse tangent function is applied

329 to the ratio and results in a non-linear normalisation with the data scaled from -1.57 to
330 +1.57 which limits the affects of outliers and potentially infinite values (IAEA, 2003;
331 Schetselaar, 2002).

332 2.2. Fuzzy feature extraction

333 The data processing discussed in this section concerns the gridded raster data used for the
334 input variables of the modelling. The data processing was conducted in ArcSDM 5,
335 maintained by the Geological Survey of Finland (GTK, 2019), which compiles various tools
336 for mineral prospectivity modelling. It includes the ROC curve tool that is used for data
337 assessment and validation. The first machine learning prospectivity model uses the initial
338 standardised variables. The second model uses fuzzy-transformed variables that required
339 further processing, using guided fuzzy set theory. The aim of this is to assess whether
340 combining user-knowledge through fuzzy membership and fuzzy operator transformation
341 enhances model performance.

342 2.2.1. Fuzzy membership transformation

343 The subjective nature of fuzzy set theory and the Fuzzy Logic method can be circumvented
344 by refining input variables using the ROC curve tool developed by Nykänen et al. (2015,
345 2017). The approach provides a quantitative metric for assessing subjective aspects of the
346 Fuzzy Logic technique, namely the application of the fuzzy membership function and fuzzy
347 operators such as *FuzzyOR* (An et al., 1991; Bonham-Carter, 1994). The tool optimises the
348 output of these functions and operators and at the same time provides information on the
349 spatial correlation of input variables with known deposits. In turn, the correlation of an
350 input layer can be used to indicate whether it is correctly included as part of the conceptual
351 deposit model. Further, by repeating the ROC curve analysis 10 times, Nykänen et al. (2017)
352 demonstrate that a more robust metric is obtained that highlights the variability in the AUC
353 statistic when using randomly generated non-deposit samples.

354 The method applied here used an iterative approach to assess the fuzzy membership
355 function using the ROC curve tool and refine each input variable. The fuzzy membership
356 function transforms initial evidence layers by determining a *spread* and *midpoint*. Once a
357 variable was determined to be ascending or descending; e.g. the target values are small or
358 large, respectively, the *spread* and *midpoint* was optimised to create a layer with the best
359 AUC value. Note that the Proximity-to Granite in Z was generated using the Table of
360 Contents (TOC) function from the ArcSDM 5 package. A list of the final input variables and
361 the optimised parameters used for the fuzzy membership functions is given in Table 2. A
362 complete table of all the iterations generated is presented in the Supplementary
363 Information (S1).

364 The averaged results of 10 different ROC curve analyses provides a robust metric for
365 determining the validity of the applied fuzzy membership function. It is clear that some
366 input variables have a much higher AUC than others. Nykänen et al. (2017) suggest there is
367 value in the inclusion of a variable even where AUC values are close to 0.5 (random
368 correlation) because it may provide mutually beneficial information to a subsequent
369 combination of variables later in the analysis, e.g. through fuzzy operators.

370 2.2.2. Fuzzy operator combinations

371 Following fuzzy membership transformation, some input variables were combined into
372 single layers to not only enhance the variable but to also assist with dimensionality
373 reduction in the model. Elements with geochemical analyses in the form of both soil and
374 stream-sediment data were integrated into single variables to represent the overall
375 anomalies for that element (Figure 7). The same approach was also applied to geochemical
376 ratios, with the exception of K/(Zr/Eu) as this was only created from stream-sediment
377 geochemistry due to the omission of REE analysis for the soil data. A visual inspection of the
378 data was conducted prior to integration to ensure that values in each variable were
379 comparable.

380 The *fuzzyOR* operator is considered to be the best tool to combine two elements or ratios
381 into a single input variable to maximise potential anomalies (Bonham-Carter, 1994) and
382 reduce dimensionality in the model and it is used here to maximise indications of
383 geochemical anomalies from both datasets. These were subsequently reassessed using the
384 ROC curve tool and new AUC values were calculated (Table 3). For W, Sn, As and Na, this
385 results in a synergistic effect where the AUC is greater than both AUC values for the
386 individual datasets. For Bi, Sb, Rb, Cs, K/Cs, K/Rb and Ti/Sn, the AUC values fall between the
387 lower and upper values derived for the original datasets.

388 2.3. Machine learning methods

389 Various MLAs are available for prospectivity modelling, however, it is the Random Forest
390 algorithm that has consistently proven to be highly effective in comparison to Support
391 Vector Machines and Artificial Neural Networks (Carranza and Laborte, 2016; Emmanuel
392 John M. Carranza and Laborte, 2015a, 2015b; Rodriguez-Galiano et al., 2015; Sun et al.,
393 2019). For this reason, two Random Forest models are presented for prospectivity
394 modelling, one using standardised variables with no transformation and the other using
395 variables transformed using the guided fuzzy set theory approach of Nykänen et al. (2015,
396 2017). An advantage of the machine learning approach to mineral prospectivity modelling is
397 the evaluation metrics available for each algorithm. Many classification methods allow the
398 probability of a pixel being correctly classified (the class probabilities) to be interrogated.
399 For mineral prospectivity modelling, class probabilities are often presented as the final
400 result but these can be further manipulated through model variance (Cracknell and Reading,
401 2013; Kohavi and Wolpert, 1996) to evaluate the model using a newly derived Confidence
402 Metric.

403 2.3.1. Training and validation data

404 A set of known tungsten occurrences was compiled from the Mineral Occurrence Database
405 maintained by the BGS GeoIndex (2018). A total of 34 known tungsten occurrences are
406 recorded in the region and were used as true positive samples. These true positive samples
407 were randomly subset 70:30 into 23 training and 11 validation data.

408 True negative samples are also necessary to accurately model and validate unfavourable
409 areas. An equal number of true negative samples were generated to ensure balanced
410 training classes and minimise error rates (Mellor et al., 2015). These samples were created
411 through random sampling of the study area as outlined by Nykänen et al. (2015). A

412 minimum buffer of 400 m was applied to minimise spatial correlation with either true
413 positive samples, or other true negative samples. Furthermore, 10 different sets of random
414 samples were generated to assess the effect of randomisation on the validation results as
415 suggested by Nykänen et al. (2017). Therefore, the procedure of validation is to combine the
416 true positive samples with a different set of true negative samples 10 times and
417 subsequently calculate the mean, median and standard deviation of the AUC results. This
418 approach provides information on the variability caused by random points and of sensitivity
419 whilst minimising the chance of a biased true negative sample set affecting model
420 validation. The 10 sets of 34 true negative samples were merged and subset 70:30 into 23
421 training and 11 validation data per set. Training data from the first random set were
422 included in the modelling.

423 2.3.2. Prospectivity modelling

424 Prospectivity modelling was performed using a combination of GIS, the ArcSDM package
425 and the *R* statistical computing language (R Core Team, 2019). A binary MLA classification
426 model was created where two classes were used (unfavourable and favourable) to
427 determine a simple class probability model. MLA models were implemented using the *caret*
428 (Kuhn et al., 2019), *raster* (Hijmans, 2019) and *rgdal* (Bivand et al., 2019) packages. A full
429 description of the *R* workflow is presented in the Supplementary Information (S2).

430 The Random Forest method is an ensemble decision tree machine learning algorithm
431 (Breiman, 2001). The approach combines multiple binary-split trees which limits overfitting
432 that can occur through multi-split trees (Hastie et al., 2009). The Random Forest algorithm
433 utilises multiple randomised decision trees (the forest) where the random effect is
434 controlled by the user-defined *mtry* value; a means of subsetting the input variables used to
435 initiate the trees (Breiman, 2001). The *mtry* value can be defined using a random or grid
436 search to find the best value, or by calculating the square root of the number of input
437 variables (Belgiu and Drăguț, 2016; Breiman, 2001; Gislason et al., 2006). A further
438 parameter must be set, *ntree*, which dictates the number of binary trees in the forest and
439 controls the reproducibility of the results. Based on a review by Belgiu and Drăguț (2016),
440 *ntree* is commonly set to 500 for most classification problems using remote sensing data.
441 Emmanuel John M. Carranza and Laborte (2015b) increased *ntree* to 20 000 in order to
442 achieve stable predictions and lower the prediction error for a training set of 12 samples.
443 Given the comparably small training sample size in this study (23 training samples and 11
444 validation samples), the *ntree* value of 20 000 was adopted for this study.

445 A total of 28 variables are included in the standardised model (see Table 2) and 17 included
446 in the fuzzy-transformed model whereby all duplicate geochemical elements have been
447 combined using the *fuzzyOR* operator (see Table 3). All fuzzy-transformed and combined
448 data were included in the modelling process despite the potentially low relevance of Sb. The
449 inclusion of Sb is due to its minor positive correlation with known deposits that may still
450 contribute some relevant information.

451 2.3.3. The Confidence Metric

452 Spatial evaluation of the model can be undertaken by calculating the model variance
453 (Equation 3) of the class probabilities to derive an uncertainty value (Kohavi and Wolpert,
454 1996). The technique was implemented by Cracknell and Reading (2013) to show areas

455 where the classification is less reliable. In this study, model variance is exploited to
456 determine whether favourable targets are truly robust in the mineral prospectivity model.
457 By combining model variance and the class probabilities into the new Confidence Metric
458 using Equation 4, exploration targets can be refined to highlight the areas of highest
459 confidence in the model.

$$460 \quad \text{model variance } (v) = \frac{1 - \sum p_c^2}{1 - \sum \left(\frac{1}{c}\right)} \quad (3)$$

461 Where p_c is the class probability for each class per pixel and c is the total number of classes.

$$462 \quad \text{confidence } (p_{conf}) = \frac{(p_c - v)_i - \min(p_c - v)}{\max(p_c - v) - \min(p_c - v)} \quad (4)$$

463

464 Where i indicates a per pixel subtraction.

465 By subtracting the model variance, the values of pixels with high uncertainty are reduced
466 accordingly, leaving only the most reliable areas with high class probabilities. In some cases,
467 this can reduce the value to less than zero and, for the purposes of comparison, Equation 4
468 normalises the output to a range of 0 to 1.

469 2.3.4. Areal evaluation

470 The spatial distribution of the prospectivity is quantitatively evaluated using areal analysis.
471 Total areal extents are calculated for each level of prospectivity (unfavourable through to
472 highly favourable) as a sum of the area for each level and as a percentage of total area of
473 the model. The analysis provides a quantitative assessment of the spatial distribution of the
474 class probabilities for each model and the associated confidence. The proportion of pixels at
475 each prospectivity level are compared to determine which model is better at discriminating
476 prospective areas.

477 2.3.5. Depth evaluation

478 The rich mining history of SW England means that there is an extensive repository of data
479 but the quality of digital records is highly variable. Legacy mining data is available through
480 the British Geological Survey from the Mineral Exploration & Investigation Grants Act
481 (MEIGA) records and published works such as Dines (1956). These resources are used to
482 further evaluate the depth at which deposits may occur.

483 3. Results and Discussion

484 The results of the MLA modelling using both feature extraction methods are presented
485 below. These are assessed based on the AUC values from ROC curve analysis and further
486 evaluated using the Confidence Metric, areal analysis and legacy mining data. These
487 evaluation techniques, respectively, aim to generate robust targets, compare the spatial
488 attributes of the model and to give an indication of whether targets are likely to reside at
489 surface or at depth.

490

3.1. Tungsten prospectivity modelling results

491 The results of the modelling using standard and fuzzy input variables are presented in
492 Figure 8 and Figure 9. Each figure comprises the binary classification of all prospective areas,
493 the class probability for a cell being classified as prospective and the confidence map
494 derived using the Equation 4.

495 The class map for the prospectivity model shows broad areas of prospective areas for
496 tungsten mineralisation due to the binary classification. The Random Forest class probability
497 map is therefore more useful as it demonstrates the likelihood that a location is prospective.
498 For Figure 8 and Figure 9, the data have been categorised to show only values greater than
499 0.5 in colour, this is to indicate that anything below this value would have been classified as
500 unfavourable in the binary classification.

501 The class probability map for the standardised variables (Figure 8) shows a good correlation
502 with known tungsten occurrences. Areas of high favourability are constrained to areas of
503 known deposits marked as W-Y in Figure 8b, which include the Camborne-Redruth district,
504 the St Austell district and the east Bodmin-Kit Hill area, respectively. However, no highly
505 favourable areas are identified that were not previously known and only limited areas have
506 been identified as favourable.

507 Figure 9 shows the class probability map for the fuzzy-transformed variables that identifies
508 highly favourable areas over known tungsten occurrences similar to those in Figure 9b
509 including the Cligga Head (Z) and the margin of the north Bodmin Granite (E). Additional
510 areas include the Breage district (A), the southern margin of the Bodmin Granite (B) and
511 some discrete targets along the eastern margin of the Dartmoor Granite (C) which are new
512 prospects. The map also shows broader areas of favourable prospectivity away from main
513 targets which are of interest.

514 The ROC curve tool was used to validate these models and generate a quantitative measure
515 of accuracy for the binary classification. A summary of the validation results from the ROC
516 curve analysis is included in Table 4. The average AUC values for both class probability
517 models are very high and not significantly different. It is unsurprising that both models have
518 such similar AUC values due to sharing the same initial evidence layers and the invariance of
519 the Random Forest algorithm to changes in scale imparted by the fuzzy membership
520 transformation. Furthermore, the similarity in AUC values underlines that the use of training
521 samples with the ROC curve tool during feature extraction has not overly biased the model.
522 However, the reduction in dimensionality from 28 to 17 input variables in the fuzzy-
523 transformed model appears to have provided no significant improvements to the modelling.

524 Despite the minimal difference in AUC values, the lack of new highly prospective targets in
525 the standardised variable model is disappointing. Nevertheless, the greater number of new
526 targets in the fuzzy-transformed model indicates that the incorporation of user-knowledge
527 through fuzzy-transformed variables during feature extraction has refined target
528 identification within a data-driven Random Forest modelling approach.

529 3.2. Target confidence

530 The use of model variance (Equation 3) has been demonstrated by Cracknell and Reading
531 (2013) where areas of high variance were spatially correlated with fault zones between
532 classified lithologies. Here, the uncertainty associated with model variance is manipulated
533 using Equation 4 and transformed into a measure of confidence for potentially prospective
534 areas.

535 The confidence maps for each model shown in Figure 8c and Figure 9c reveal highly
536 favourable and favourable areas that are not only significantly refined in area, but define
537 more reliable targets. Any area shown to be >0.5 in terms of confidence should be
538 compared to the class probability map to determine its favourability and those areas with
539 high class probabilities and high confidence are likely to be robust. Therefore, the
540 confidence map helps to elucidate highly favourable and favourable areas and interpret
541 reliable exploration targets.

542 3.3. Model comparison from areal evaluation

543 The two Random Forest models presented here can also be assessed to determine the
544 prospectivity by area. Models for class probability and confidence have been assessed in
545 terms of area in Table 5. These show the total area and normalised area for each class
546 shown in Figure 8 and Figure 9.

547 The total areas are similar for each model and small discrepancies are due to rounding
548 errors. The class probability model for standardised variables shows a greater proportion of
549 the study area having some degree of prospectivity (>0.5). In contrast, the class probability
550 model for the fuzzy-transformed variables shows a smaller proportion of the study area to
551 be prospective (>0.5) but the areas that are identified have a greater degree of
552 prospectivity; the most prospective areas (>0.8) accounts for 3.7% of the total area
553 compared to 2% when using standardised variables. Similarly, the confidence model for
554 both methods has been assessed. If a value of >0.5 is taken as a reasonable confidence level,
555 3.2% and 5.2% of the models for standard variables and fuzzy-transformed variables,
556 respectively, can be considered to be robust.

557 The results from this analysis would infer that the fuzzy-transformed variables give an
558 overall greater confidence when generating exploration targets compared to the
559 standardised variables. By revisiting Table 3, it can be seen that the combination of W, Sn,
560 As and Na has a mutually beneficial effect on the AUC values compared to the prior values
561 for the individual soil and stream-sediment geochemical layers. These mutually beneficial
562 combinations are likely to improve the MLA model and enhance target delineation.

563 Evaluation using legacy mining data

564 New targets were identified from the Random Forest model using fuzzy-transformed
565 variables. These include the Breage district, the southern margin of the Bodmin Granite and
566 some discrete targets along the eastern margin of the Dartmoor Granite labelled A, B and C,
567 respectively (Figure 9b). These are further highlighted in Figure 10 alongside additional
568 legacy data to further assess the fuzzy-transformed variable model.

569 In the Breage district (Figure 10a), historic mining records indicate tungsten mineralisation
570 was intersected at depth at Prospidnick on the SW margin of the Carnmenellis Granite and
571 at Great Wheal Fortune on the eastern margin of the Tregonning-Godolphin Granite (Dines,
572 1956). Furthermore, a borehole was drilled in the area that intersected tungsten and tin
573 mineralisation (Ball et al., 1984); this is also missing from BGS GeoIndex (2018).

574 Studies conducted under MEIGA are not recorded in the BGS GeoIndex (2018). The
575 mineralisation along the southern margin of the Bodmin Granite (Figure 10b) was
576 investigated by Consolidated Gold Fields Ltd as part of regional tungsten exploration study
577 funded by MEIGA in 1972. Tungsten and tin anomalies were identified in streams and
578 follow-up soil sampling was also conducted. A drilling campaign along the southern margin
579 of the granite was conducted which intersected tungsten mineralisation but grades and
580 tonnages were deemed uneconomic at the time.

581 Targets identified in Figure 10c along the eastern margin of the Dartmoor Granite require
582 further follow-up work. No records of tungsten have been found, however, four mines are
583 inferred by Dines (1956) to become uneconomic with depth with respect to tin and it was
584 suggested that other “uneconomic” metals may exist but are not described further. One of
585 these mines exists outside of the surface crop of the granite and intersects the granite
586 margin at approximately 90 m below surface.

587 The use of these additional resources helps validate the mineral prospectivity model. The
588 reference to tungsten mineralisation found in old mines and former drilling projects
589 suggests that some of these targets may be within a few hundred metres of surface. This
590 further supports the model for identifying blind deposits and the inclusion of the proximity-
591 to granite in Z evidence layer is likely to be important and high resolution gravity
592 measurements may improve the analysis significantly.

593 Conclusions

594 Mineral prospectivity modelling has been conducted using a data-driven Random Forest
595 MLA approach for tungsten in SW England. A particular focus has been put on feature
596 extraction and the use of initial variables that were standardised to zero mean and equal
597 variance compared to those that were further processed using knowledge-driven fuzzy
598 membership and fuzzy overlay functions.

599 The two models presented here have similar accuracies based on ROC curve analysis but
600 show different spatial distributions of prospectivity in the region. The model that uses
601 standardised variables only identifies areas of high prospectivity (>0.9) proximal to the
602 training data. The second model, using fuzzy-transformed input variables, identifies three
603 new highly prospective targets that were previously unidentified in the training data. The
604 improvement in target generation is directly attributable to the use of knowledge-driven
605 feature extraction techniques within a data-driven MLA framework.

606 These models are enhanced using model variance to derive a new Confidence Metric. The
607 Confidence Metric is a simple calculation to infer where class probabilities are most robust.
608 These are presented as a map that can be combined with the initial class probabilities to

609 determine the most reliable targets. The approach results in spatially refined and robust
610 mineral exploration targets that can allow for a more focus follow-up field campaign.

611 The models have been further evaluated by an areal analysis showing that the fuzzy-
612 transformed model is a better discriminator for prospective areas compared to the
613 standardised variable model due to the mutually beneficial effect of combining geochemical
614 layers such as W, Sn, As and Na during feature extraction. Also, the fuzzy-transformed
615 model has greater confidence and generates greater proportion of robust targets by area
616 based on the Confidence Metric. By conducting model evaluation in this way, two models
617 with the same statistical accuracy but different spatial distributions can be better
618 understood. This study underlines how single accuracy metrics can be fallible when applied
619 to spatial datasets.

620 Finally, the use of legacy mining data further reinforces the strength of the model where all
621 three new target areas have potential economic mineralisation either through direct
622 sampling or inferred from mine descriptions. Further, the legacy mining data suggests that
623 the targets generated may be within 300 m of surface. This would indicate the “Proximity-to
624 granite in Z” evidence layer derived from regional gravity data is valuable and that new
625 discoveries of tungsten mineralisation in SW England may be enhanced by a new high
626 resolution gravity survey.

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897 **Figure Captions**

898 *Figure 1: Summary geology of SW England showing Devonian-Carboniferous sedimentary*
899 *host rock in grey, granite outcrop in red and depth-to granite contours based on the granite*
900 *surface model by Willis-Richards and Jackson (1989). Black lines represent regional*
901 *lineaments derived by Yeomans et al. (2019) from Tellus South West airborne geophysical*
902 *data.*

903 *Figure 2: Schematic illustrations of the kinematics and structures generated during Permian-*
904 *Triassic extension (D3-D6). After Shail and Alexander (1997).*

905 *Figure 3: Schematic outline of extractive areas in SW England showing tin, copper and*
906 *tungsten. Data from BGS GeolIndex (2018) are based on historic production values from*
907 *known mines, deposit and prospect localities as well as reported mineral showings and*
908 *panned concentrates. Important tungsten producers are labeled based on data from Dines*
909 *(1956) and Jackson et al. (1989). Key mining areas are highlighted on the map: a = St Just, b*
910 *= Camborne-Redruth, c = Breage, d = St Austell, e = Bodmin, f = Tamar Valley.*

911 *Figure 4: Mineral prospectivity modelling workflow for combining knowledge-based feature*
912 *extraction into a data-driven machine learning approach to generate spatially refined and*
913 *robust targets for mineral exploration.*

914 *Figure 5: Conceptual deposit model for tungsten mineralisation in SW England showing the*
915 *main geological phenomena targeted by the prospectivity modelling.*

916 *Figure 6: Granite geochemistry showing the distribution of granite types based on the*
917 *classification by Simons et al. (2016). The G2 granite is distinct having a low Zr/Eu ratio and*
918 *high K, however, the G1a granite shows a similar signature.*

919 *Figure 7: (A) interpolated stream-sediment geochemical data for tungsten that have been*
920 *transformed using the fuzzy membership function. (B) interpolated soil geochemical data for*
921 *tungsten that have been transformed using the fuzzy membership function. (C) resulting*
922 *tungsten geochemical data that have been combined using the fuzzyOR operator to*
923 *emphasis key anomalies.*

924 *Figure 8: (A) Classification map (B) Class probability map and (C) confidence map for the*
925 *standardised variables Random Forest prospectivity model. Classes show the two class*
926 *scenario where 1 is unprospective and 2 is prospective. The class probability and confidence*
927 *models are categorised to show 0.9 to 1 as highly favourable (red), 0.8 to 0.9 as favourable*
928 *(amber), 0.65 to 0.8 as less favourable (turquoise), 0.5 to 0.65 as possibly favourable (blue)*
929 *and <0.5 as unfavourable (grey).*

930 *Figure 9: (A) Classification map (B) Class probability map and (C) confidence map for the*
931 *fuzzy-transformed variables Random Forest prospectivity model. Classes show the two class*
932 *scenario where 1 is unprospective and 2 is prospective. The class probability and confidence*
933 *models are categorised to show 0.9 to 1 as highly favourable (red), 0.8 to 0.9 as favourable*
934 *(amber), 0.65 to 0.8 as less favourable (turquoise), 0.5 to 0.65 as possibly favourable (blue)*
935 *and <0.5 as unfavourable (grey).*

936 *Figure 10: Key target locations based on the class probability map from the fuzzy-*
937 *transformed variables model. The Breage district is shown in (A) where drilling projects and*
938 *mining legacy data are shown to validate the targets. Targets around the Bodmin Granite*
939 *are shown in (B) with new areas validated by a drilling report. The eastern margin of the*
940 *Dartmoor Granite is shown in (C) where mining legacy data are proximal to favourable*
941 *targets.*

942

943 **Table Captions**

944 *Table 1: Geochemical data included as evidence for tungsten mineralisation. The*
945 *geochemistry are grouped into three phenomena describing the mineralisation, granite*
946 *aureole and granite type.*

947 *Table 2: AUC values for evidence layers transformed using fuzzy membership functions. The*
948 *AUC values are calculated from ten ROC curve analyses using randomly generated false*
949 *occurrences.*

950 *Table 3: AUC values for combined geochemical elements and ratios, calculated from ten ROC*
951 *curve analyses using randomly generated false occurrences. These are compared to the*
952 *geochemical values for original datasets from soil and stream-sediment (SS) data. In some*
953 *cases (W, Sn, As, Na) the combination is mutually beneficial.*

954 *Table 4: AUC values for each Random Forest™ prospectivity model. Calculated from ten ROC*
955 *curve analyses using randomly generated false occurrences. The key parameters have been*
956 *included for each model.*

957 *Table 5: Area assessment for both standardised and fuzzy-transformed models. The data*
958 *have been calculated in a GIS to show the area accounted for by each class as a sum and a*
959 *percentage for both the class probability (Prob) map and confidence (Conf) maps. Small*
960 *discrepancies are attributed to rounding errors.*

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