Use of machine learning techniques on airborne geophysical data for mineral resources exploration in Burkina Faso

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SUMMARY

Recent advances in development of automated tools and machine learning algorithms based on artificial intelligence (AI) have revolutionized our interpretation approach of big data by making it faster, more objective and more reliable than tedious manual processes.

In this paper, we show results derived from machine learning applications to the recently acquired high-resolution airborne geophysical data of Burkina Faso. The results are represented as country-wide prospectivity maps for various mineral resources including gold, uranium, base metals and strategic metals.

The new mapping products indicate that Burkina Faso has a diversified and significant mineral potential.

Key words: machine learning, maximum likelihood classifier, airborne geophysics, Burkina Faso.

INTRODUCTION

Processing and interpretation of large geophysical data sets have always been a challenge due to the complex nature of the data and the huge amount of time required for their analysis. However, recent advances in development of sophisticated processing and interpretation tools and algorithms over the past decades have led to a significant gain of time in processing and interpretation of big and multiple data sets.

The use of machine learning algorithms, which are typically based on artificial intelligence (AI), has gained a flourishing popularity in various fields of geoscience due to fast and automated tedious processes for more efficiency and accuracy of results (Bandura et al., 2018). In this study, we show interpretation results of the high-resolution airborne geophysical data collected over the entire country of Burkina Faso for mineral resource exploration and targeting.

The use of machine learning algorithms based on the supervised maximum likelihood classifier and applied to the airborne magnetic and gamma-ray spectrometric data helped identify new prospective areas for a wide range of mineral resources, which include gold, uranium, base metals and strategic metals. The new prospectivity maps will serve as useful guides for selecting new exploration targets.

METHOD AND RESULTS

We apply a machine learning approach based on the Enhanced Maximum Likelihood (EML) classifier (Campbell and Wynne, 2011) to the high-resolution airborne geophysical data from Burkina Faso. The classifier uses a number of learning areas with known geophysical patterns to generate classes of similar features and patterns using the Bayesian decision rules. The used learning areas include known deposit areas and known mineralized occurrences. The outcomes from the machine learning analysis consist in prospectivity maps for various mineral resources including gold, uranium, base metals and strategic metals.

Geology of Burkina Faso

Burkina Faso lies within the Baoule-Mossi Domain of the West African Craton and consists of three major geological units (Castaing et al., 2003): (a) Paleoproterozoic basement comprised of Birimian volcano-sedimentary belts and plutonic rocks intruded by large Eburnean granitoids, underlying most of the country; (b) Neoproterozoic marine epicontinental sediments at the western and northern borders (Taoudeni Basin) and at the south-eastern border (Volta Basin), unconformably overlying the Birimian basement; and (c) small inliers of fluviatile-lacustrine Cenozoic Continental Terminal sediments in the north-western and eastern parts of the country.

The territory is a gold-rich province whose mineral potential is linked to the Birimian volcano-sedimentary belts and their intersections with major Eburnean shear zones and faults. Additionally, there are a number of non-auriferous deposits that are represented by polymetallic deposits occurring as VMS, copper-gold and copper-molybdenum porphyry deposits, manganese associated with Tarkwa volcano-sediments, diamondiferous kimberlite deposits within the Barsalogho area, iron-titanium-vanadium deposits associated with noritic gabbro, lateritic nickel-chromite-cobalt, bauxite mineralization occurring within the Neoproterozoic sediments and various base-metal mineralized veins and lenses.

Airborne geophysical data

Figure 1 is a high-resolution colour-shaded relief Reduced-to-Pole (RTP) magnetic intensity map of Burkina Faso. This most-updated county-wide map is obtained by merging data from 03 major airborne surveys that were carried out by 03 different airborne geophysical companies at different periods of time. The grid has a spatial resolution of 100 m.
Known and inferred shear zones and faults are plotted on the map. The magnetic map reveals that the overall structure of the basement is very complex and appears to be defined by two major NNE trending shear zones: the Hounde-Ouahigouya shear zone in the west and the Tiebele-Dori-Markoye shear zone in the east. These major faults divide the basement into three domains: an eastern domain cross-cut by numerous NE-striking faults and shears, a central domain, which includes arched structures of Goren and Djibo, and a western domain hosting N-to NNE-striking structural patterns. The entire country appears to be cross-cut by a dolerite dyke swarm striking mainly in the SW-NE, SE-NW and E-W directions of late Paleoproterozoic and Mesozoic ages.
Figure 2 presents a high-resolution ternary gamma-ray spectrometric image of Burkina Faso. Like the magnetic data, this country-wide radiometric image is obtained by merging the data collected during 03 major airborne surveys.

The radiometric map shows that the main auriferous Birimian volcano-sedimentary belts are clearly highlighted by their distinct spectrometric signature (dark brown) due to their low radioactive responses (Djibo, Bouroum, Goren, Oudalan and Sebba) in the north and northeast, whilst those highlighted in the western domain appear to correlate with dark red colour (Banfora and Hounde) more likely due to the their higher potassic contents.

The red zones that dominate much of the northern, southern and south-eastern parts are suggested to be associated with Eburnean potassium-rich granites, whereas the cyan zones highlighted in both the eastern and western parts are likely attributed to Eburnean tonalites (granodiorite and granite). There is a highly radioactive zone (bright colour) observed in the northeast (Sebba region), which is suggested to present a link to highly radioactive Eburnean syenite-pegmatite complex and carbonatites. The greenish zone that dominates the westernmost part of the country is attributed to thorium-rich Neoproterozoic sediments that unconformably overlie the Birimian basement.

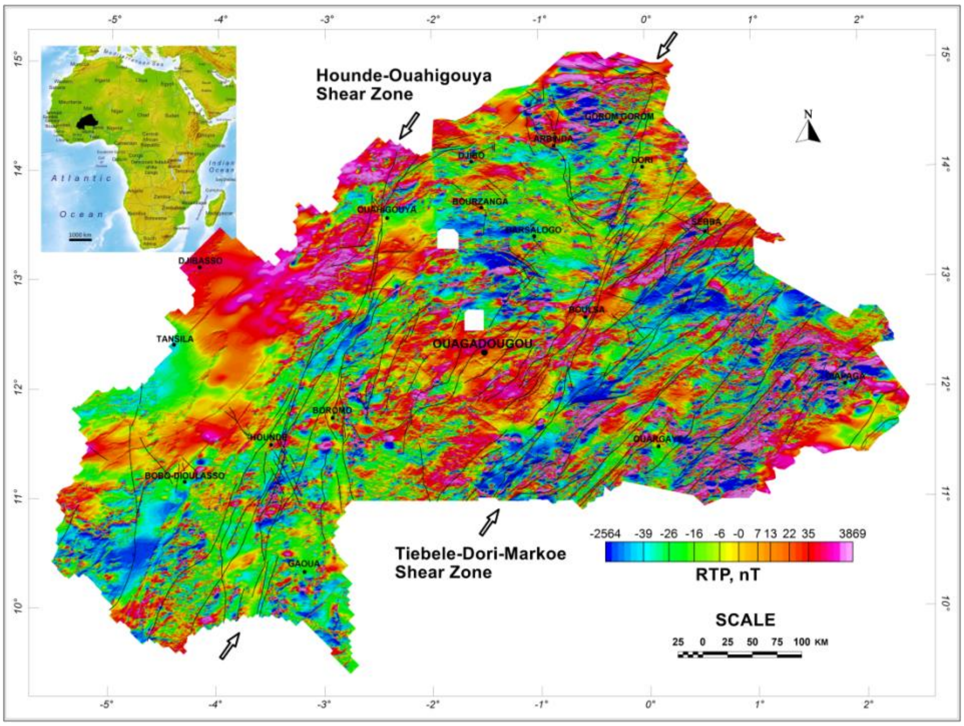

Figure 1. Colour shaded-relief RTP map of Burkina Faso including known and inferred faults.

Prospectivity mapping

The machine learning approach is applied to the airborne data to derive prospectivity maps with the aim to help and guide exploration programs for targeting various mineral resources.

The machine learning process is driven by the enhanced maximum likelihood classifier, which generates various classes presenting similar geophysical signatures and similar spectral patterns to known learning (training) areas.
Additionally, two key parameters, namely the posterior probability and the typicality index are generated and associated with each predicted data. The selected learning areas used in the machine learning process encompass known mineralized zones (deposits, mineralized occurrences and anomalous zones). 09 input datasets that include the radioelemental channels and their ratios, the RTP data and their derivatives, and 03 Landsat ETM+ images are used as input layers. An equal prior probability is assigned to each of the input layers.

Figure 3 represents the prospectivity map for uranium and REE mineralization. The training areas used for uranium and REE mineralization include known uranium occurrences in the Neoproterozoic sediments (unconformity-contact related type) of the Taoudeni basin in the north and uranium and REE mineralized occurrences in the highly-radioactive alkaline intrusions in the basement rocks (Sebba region in the northeast).

The derived from machine learning prospectivity map indicates that the eastern domain is highly prospective for uranium and REE mineralization types. Uranium mineralization is suggested to be hosted by syenite-pegmatite and young granite complexes, whereas REE mineralization is suggested to be linked to carbonatite intrusions.
From these results, the southern part of the eastern domain, which is poorly explored, appears to present a high prospectivity for both uranium and REE mineralization.

Figure 4 is the prospectivity map for iron ore and strategic metals (titanium and vanadium). The training areas used during the machine learning process include known iron-titanium-vanadium deposits of Tin Edia and Gouba and one titanium occurrence located in the north-eastern part of the country (Gorom-Gorom area).

The results show that additionally to the Gorom-Gorom area, where Fe-Ti-V mineralization is established, the southern part of the eastern domain appears to represent a highly favourable and prospective zone for Ti-V-Fe minerals. The highlighted favourable zones are suggested to be associated with Eburnean gabbro-noritic intrusions.

Gold targeting results for the north-eastern part of the country were previously derived from machine learning process (Bournas et al., 2016). Several training areas surrounding known gold deposits were used to train the learning process. Bournas et al., (2016) showed that zones of higher probability correlate well with the auriferous Birimian volcano-sedimentary belts that are affected or controlled by faults and shear zones and the arched structure of Goren and Djibo located in the northern part of Burkina Faso.

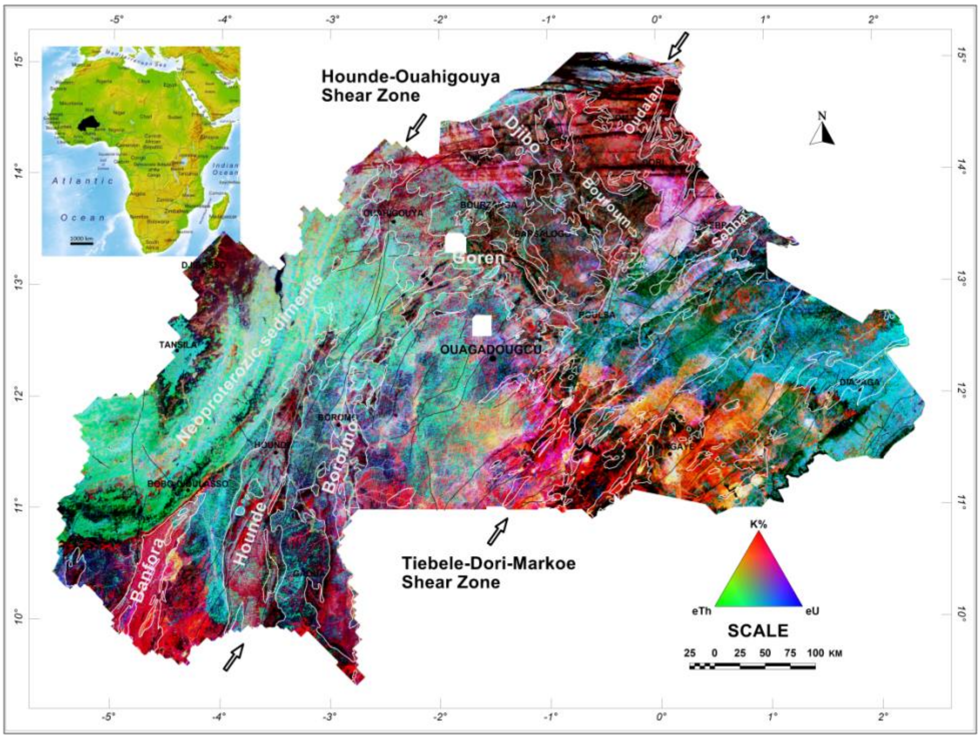

Figure 2. Ternary gamma-ray spectrometric map of Burkina Faso including the outlines of Birimian volcano-sedimentary belts and their names (in white).

CONCLUSIONS

The application of machine learning algorithm to airborne geophysical data from Burkina Faso led to the generation of regional prospectivity maps for various mineral resources.
These results suggest that the Birimian basement has a significant potential not only for gold but for other non-auriferous minerals as well including uranium and strategic metals.
The results derived from artificial intelligence processes are encouraging yet they are predictive in nature; therefore, ground verification work based on collecting and analysing ground truths are necessary to evaluate the accuracy of these results.

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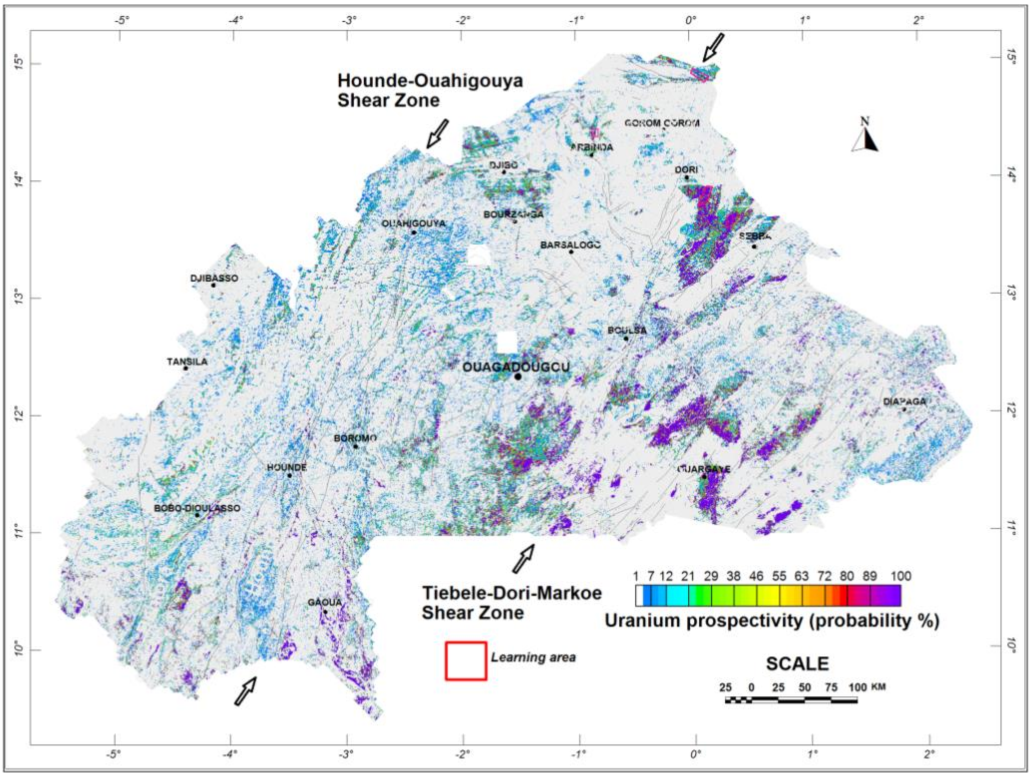

Figure 3. Prospectivity map for uranium and REE.

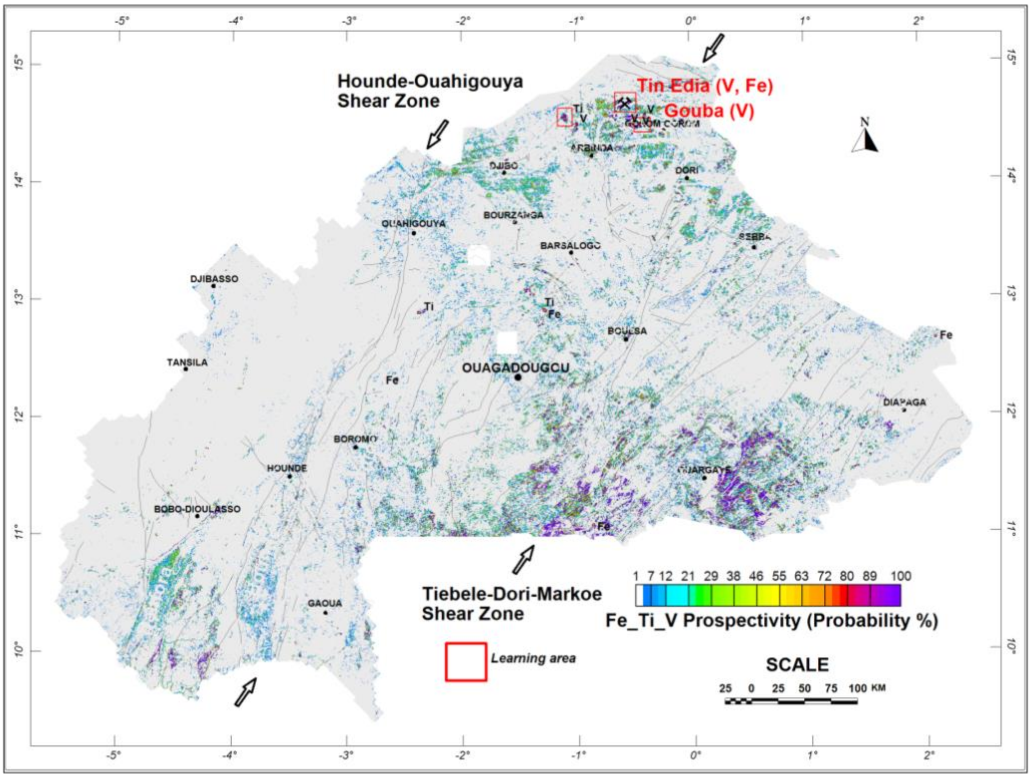

Figure 4. Prospectivity map for Fe-Ti-V.