DroneSOM

GTK radai DTU beak CONSULTANTS

Mineral predictive mapping using artificial intelligence with "advangeo® Prediction" and GisSOM software

Dr. Ina Storch (Beak), Geophysics and Software Development

Mosharof Hossain (Radai), Geology

Dr. Johanna Torppa (GTK), Geoinformatics and Information Solutions

Supported by

eit RawMaterials Connecting matters

Co-funded by the European Union

DroneSOM

1) advangeo® workflow using ANN and SOM methods
2) Test Case: The Input Data
3) Artificial Neural Network (ANN) modelling results using advangeo® 2D prediction software
4) SOM analysis using GisSOM software
5) Work procedure/Business Collaboration

Supported by

RawMaterials
Connecting matters

Co-funded by the European Union

DroneSOM

GTK radai DTU beak CONSULTANTS

1) advangeo® workflow using ANN and SOM methods

Supported by

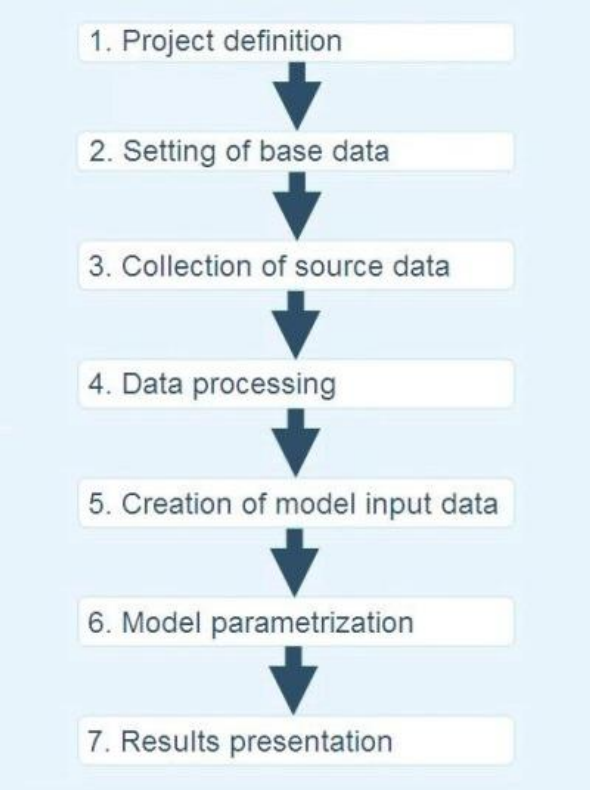
eit RawMaterials Connecting matters

Co-funded by the European Union

DroneSOM

GTK radai DTU beak CONSULTANTS

advangeo® workflow



- Prediction software, 2D and 3D, developed by Beak Consultants
- using different methods like artificial neural networks (ANN) or SOM for the prediction of spatial events and phenomena like probability of geo-hazards or location of mineral deposits
- The software covers a complete workflow for Predictive Modeling, including collection of raw data, data preprocessing and model parameterization
- GIS functionality allows data pre-processing like calculation of derivatives, distance to structures,…
- Software is constantly extended. Recently:
  - Remote Sensing Extension (2D)
  - Random Forest and SOM methods (3D)

Supported by

eit RawMaterials Connecting matters

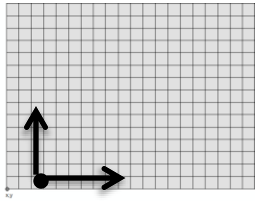
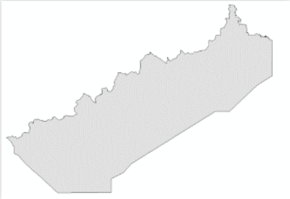
Co-funded by the European Union

DroneSOM

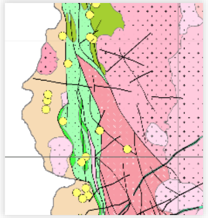
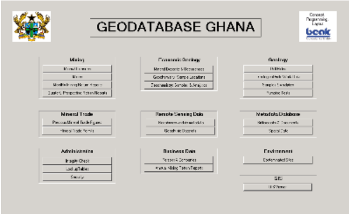
GTK radai DTU beak CONSULTANTS

advangeo® workflow

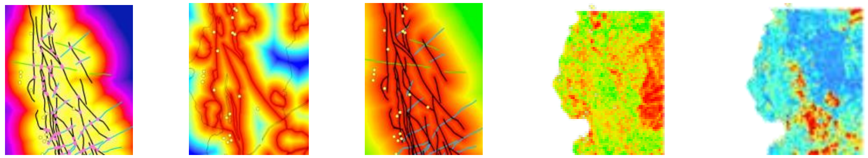
1. Project definition
2. Setting of base data
3. Collection of source data
4. Data processing
5. Creation of model input data
6. Model parametrization
7. Results presentation

Define extent, resolution (grid cell size) and projection

Different shape files and raster data, e.g. from a geo data base



Model input data,

Rasters matched to base raster, scaled

Input layers for prediction or clustering (prediction based on raster analysis)

Some with calculated neighbouring information (slope, distances, …)

Analysis methods:

ANN(MLP)

Random Forest

SOM GisSOM

Fuzzy Logic

WofE

Supported by

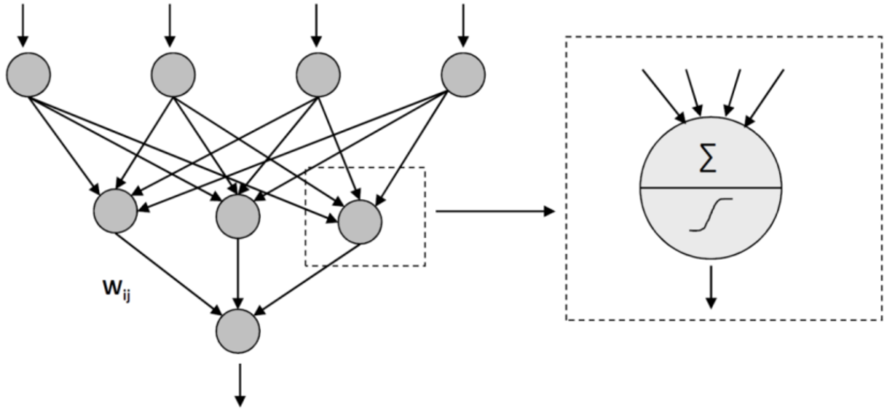
eit RawMaterials Connecting matters

DroneSOM

GTK radai DTU beak CONSULTANTS

Artificial Neural Networks (ANN)

- Network consisting of a large number of neurons that influence each other by sending and receiving information through activation signals (weights) on directed pathways
- Input data layers are weighted
- **Training data is needed**



Self Organizing Maps (SOM)

- Clustering method
  - finds clusters with similar values for the measured geodata
  - Can be used as data reduction method for further analysis/modeling
- **No training data needed**
  - Does not generate a model between observations and explanatory variables
  - Applicable for all kinds of multivariate data, also cases with data insufficient for supervised modeling methods (like ANN's)

Supported by

eit RawMaterials Connecting matters

Co-funded by the European Union

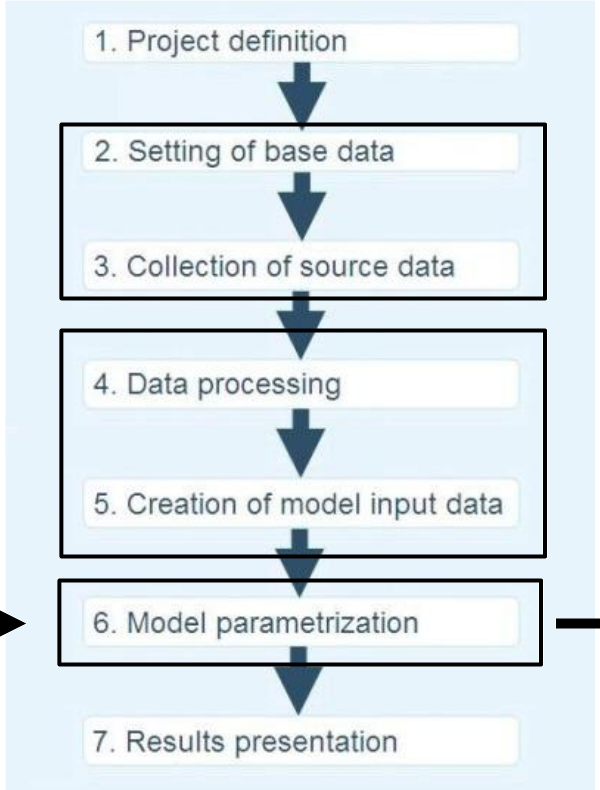
DroneSOM

GTK radai DTU beak CONSULTANTS

Advangeo® workflow

GisSOM

Study the data before modeling;
Data reduction if needed



Analysis method:
ANN(MLP)

Supported by

eit RawMaterials Connecting matters

Co-funded by the European Union

DroneSOM

2) Test Case: The Input Data

Supported by

RawMaterials
Connecting matters

Co-funded by the
European Union

DroneSOM

GTK radai DTU beak CONSULTANTS

Data sources:

- ✓ Partner company's data:
  - Lithological data
  - Geochemical data
  - Structural (tectonic) data
  - Radai drone magnetics data
    Including derivatives (e.g., 1VD, tilt gradient)

- ✓ GTK data:
  - GTK airborne electromagnetic data
  - GTK airborne radiometric data

- ✓ Optional GTK data:
  - GTK airborne magnetic data
  - GTK lithological data
  - GTK structural data
  - GTK geochemical data

Supported by

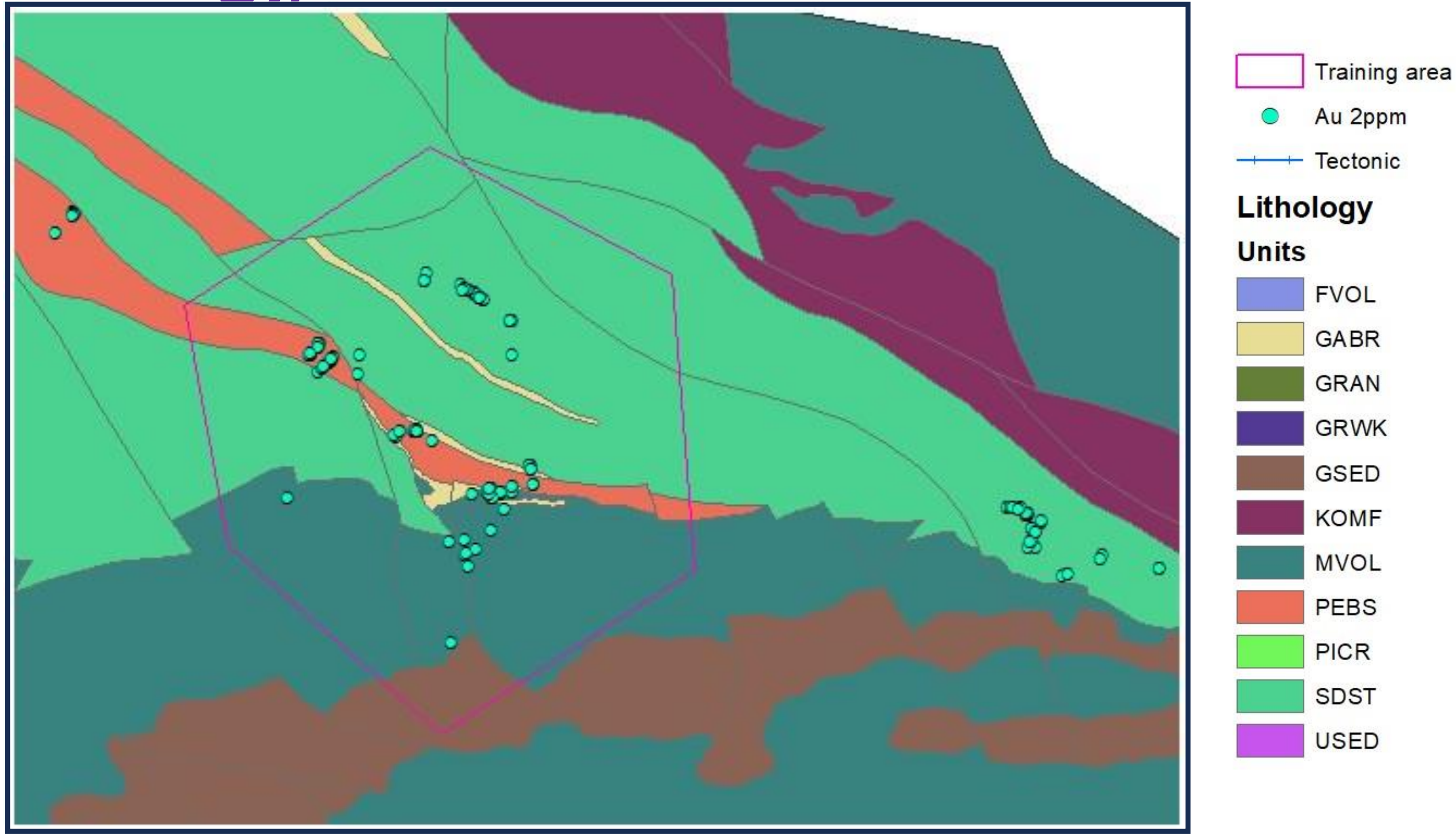
eit RawMaterials
Connecting matters

Co-funded by the
European Union

DroneSOM

GTK radai DTU beak CONSULTANTS

Lithology, tectonics and Au data:



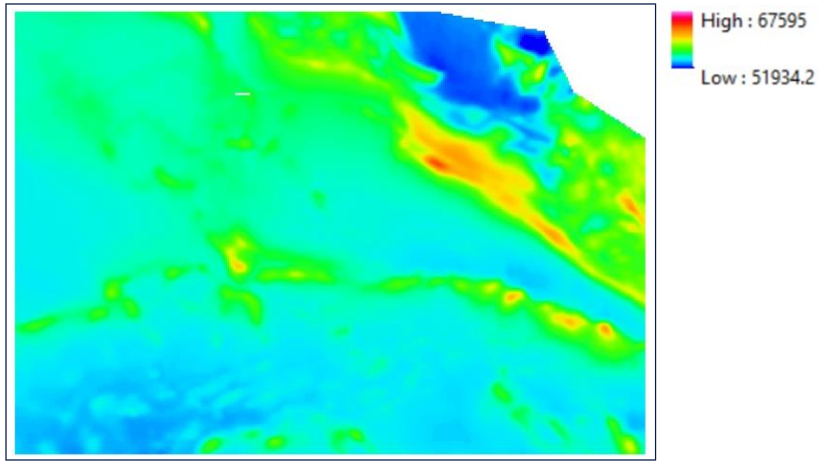
The gold data particularly from outcrop/sub-outcrop and boulder sample which have greater than 2 ppm concentration within the training area are used for preparing the prediction model for the project area.

Supported by

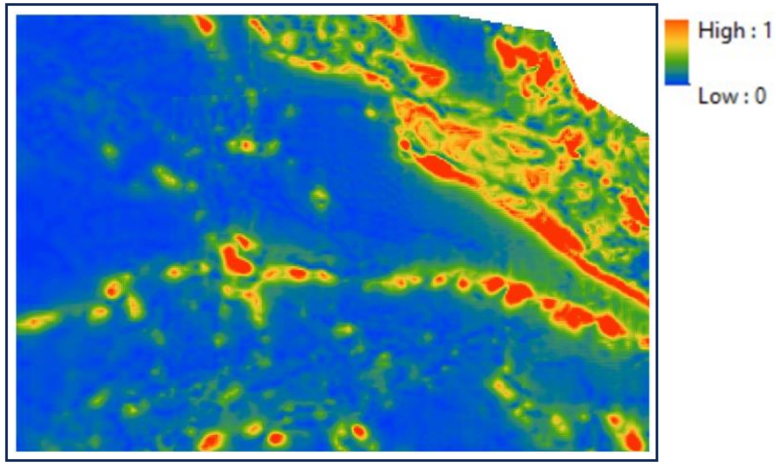
eit RawMaterials
Connecting matters

Co-funded by the European Union

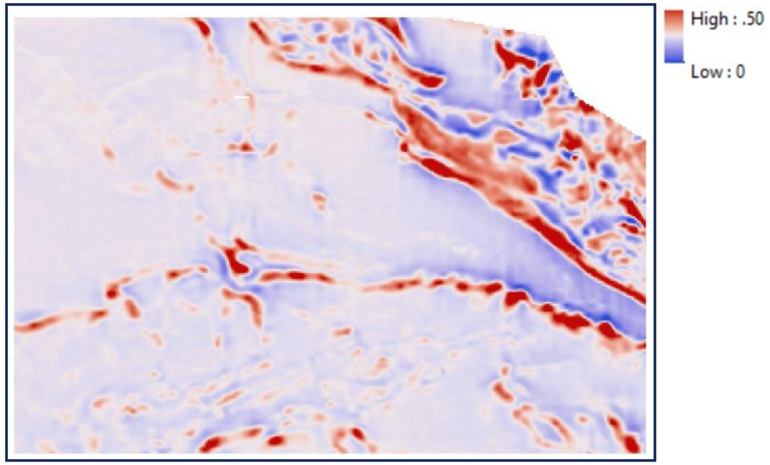
Drone magnetic data:



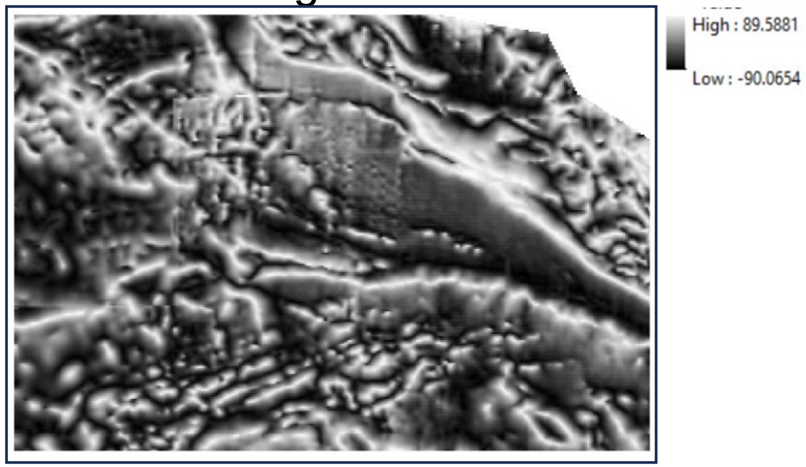
Total magnetic intensity



Total gradient

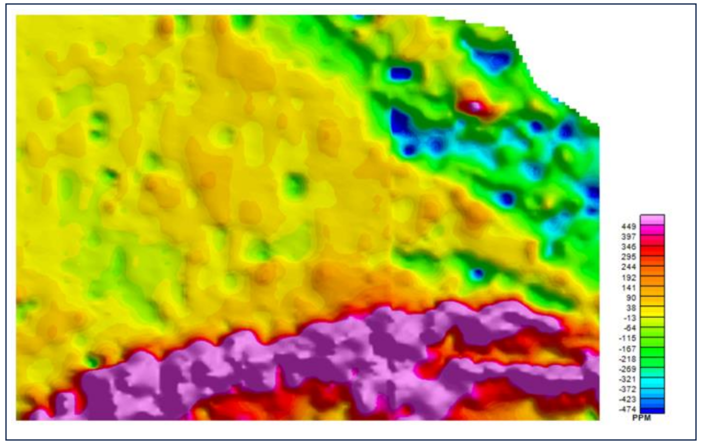


1st vertical derivative

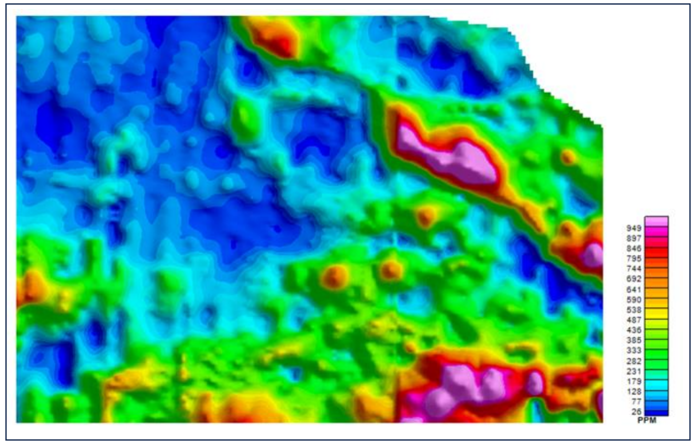


Tilt gradient

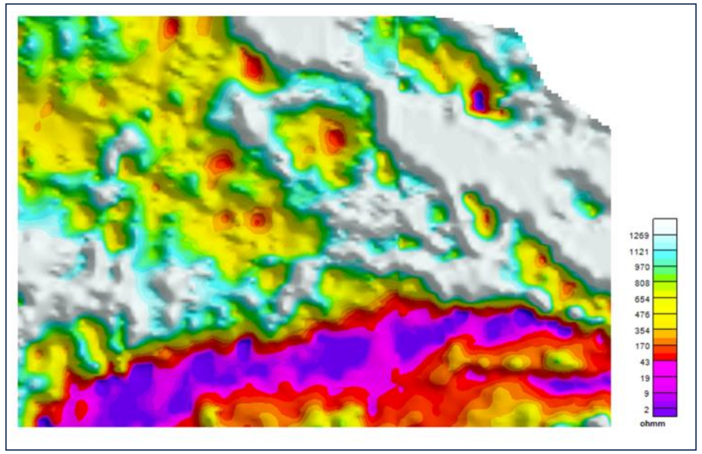
Airborne electromagnetic data:



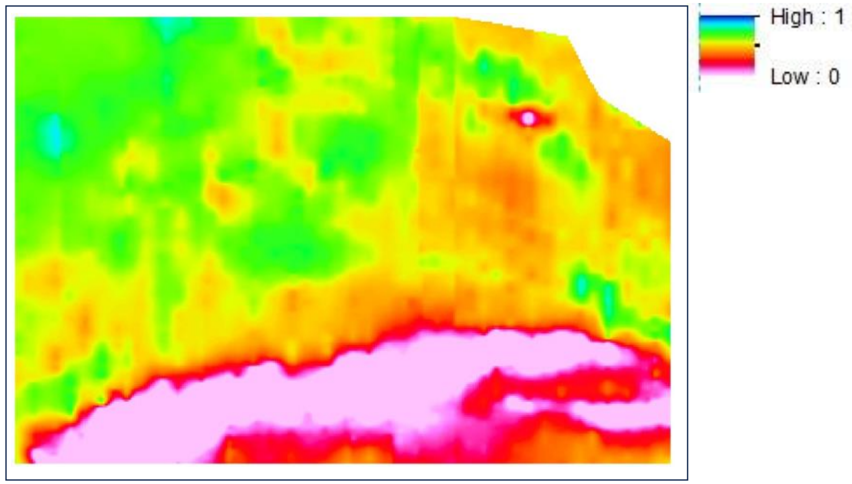
In-phase (real) component



Quadrature (imag) component

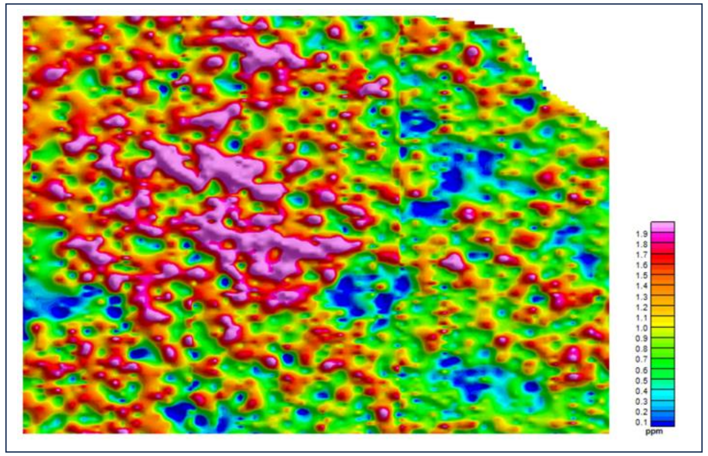


Apparent resistivity

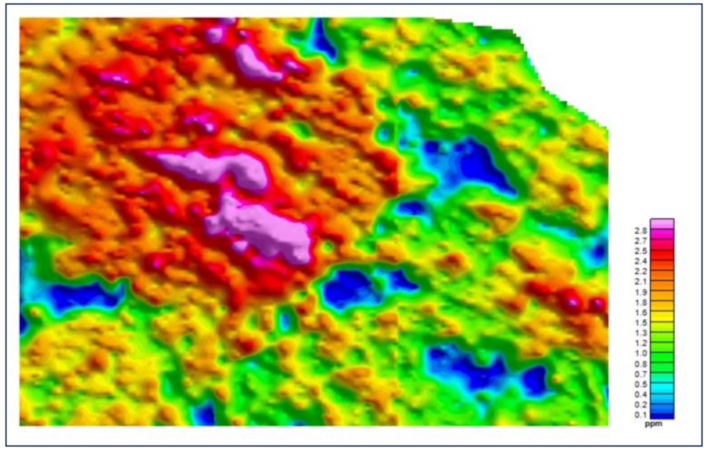


Basement resistivity (processed) from 2-layer inversion

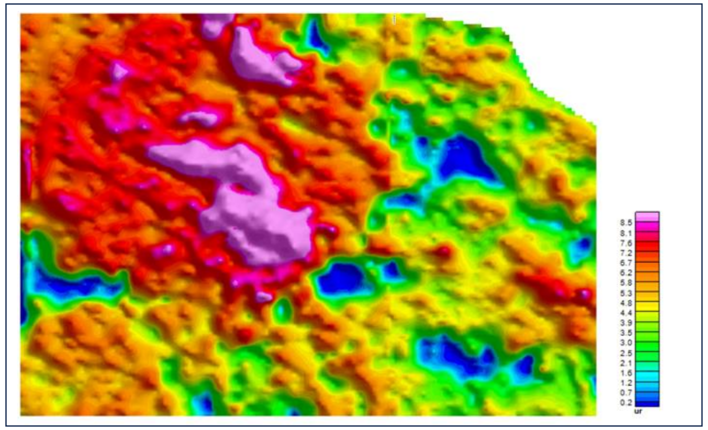
Airborne radiometric data:



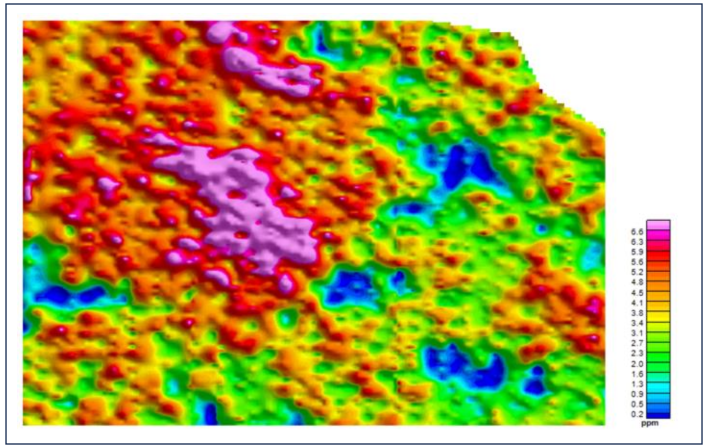
Uranium



Potassium



Total intensity



Thorium

3) Artificial Neural Network (ANN) modelling results using advangeo® 2D prediction software

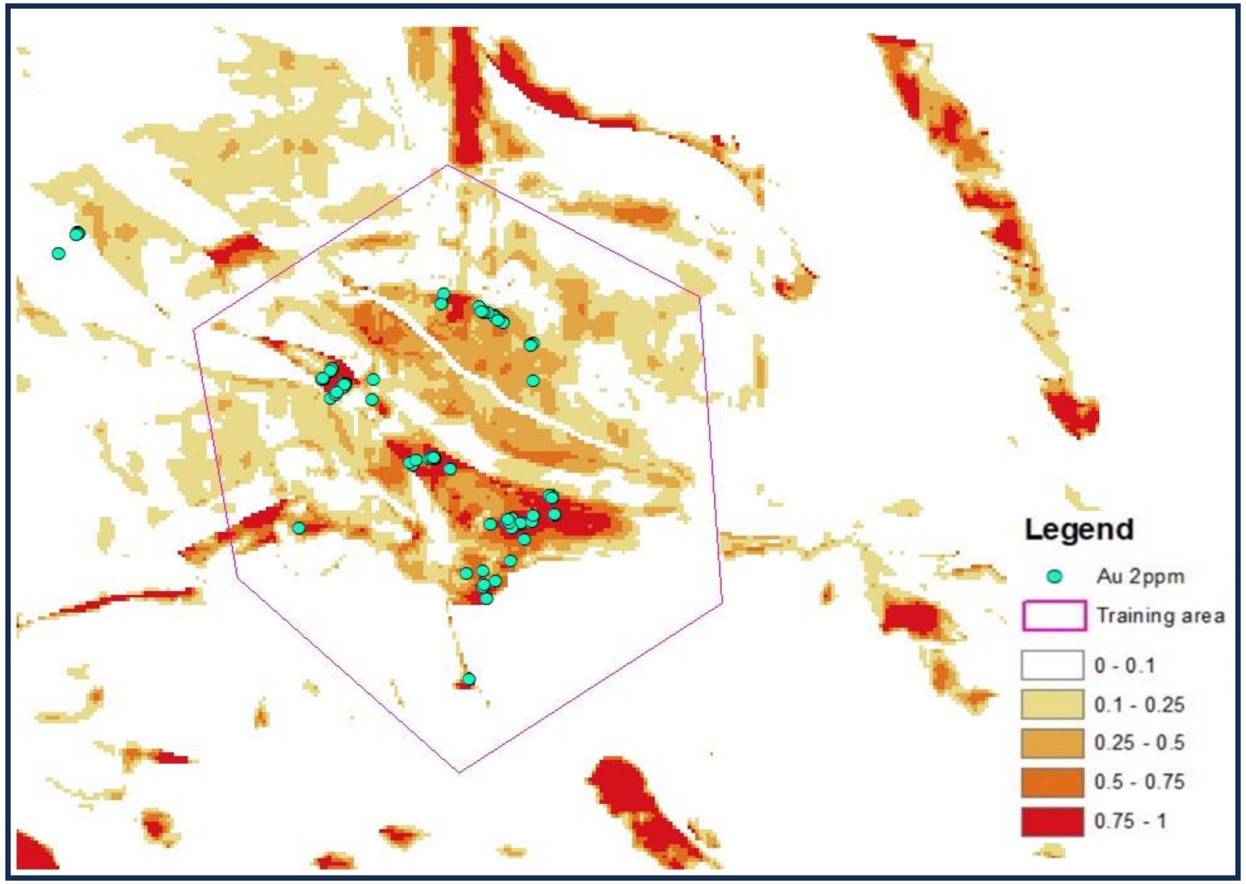
Supported by

Connecting matters

Co-funded by the European Union

Predictions:

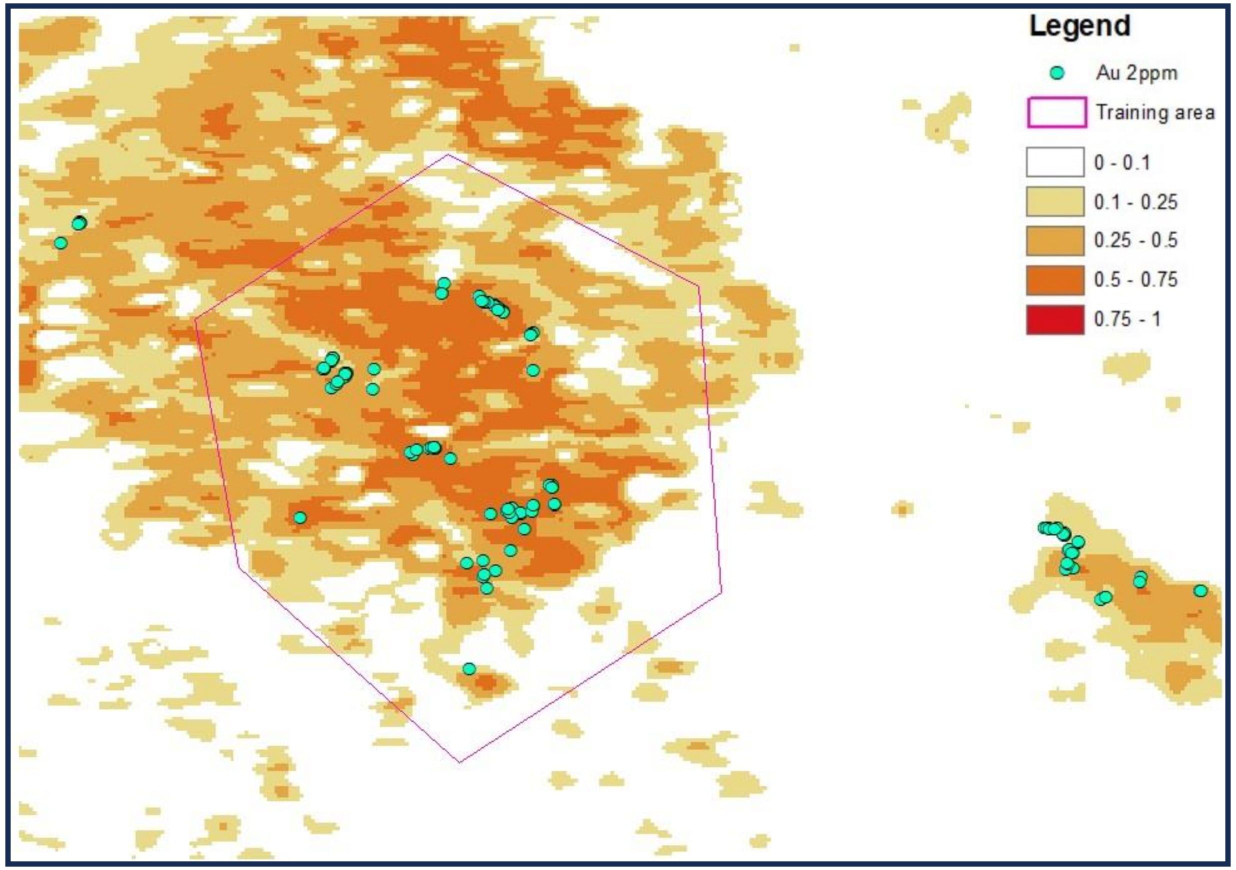
advangeo 2D software was used to prepare several predictive maps on the basis of available geophysical, geological and geochemical (Au ≥ 2 ppm in outcrops) parameters within a training area and later on outside the training area.



Gold predictive map (#25) in an area of interest

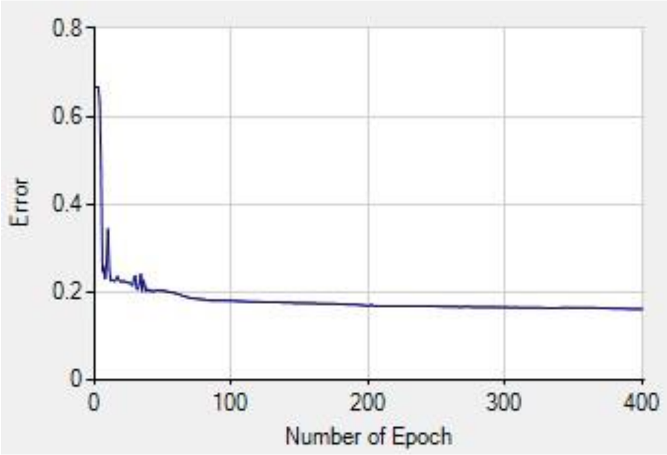
Supported by
eit RawMaterials
Connecting matters
Co-funded by the European Union

Prediction Model #19



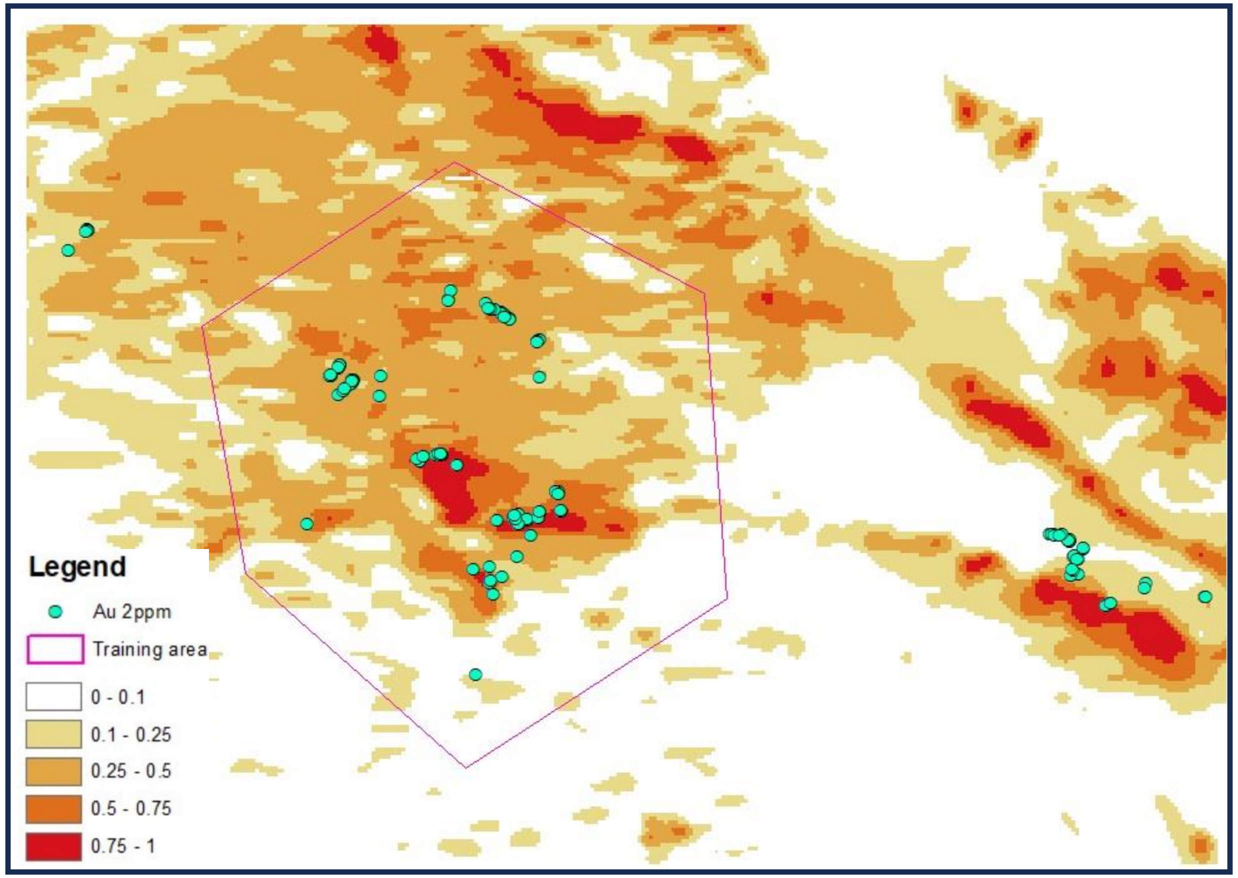
Model using GTK radiometric (U, Th, K and total) data

Name	Conn wgt
Radiometric potassium (scaled)	-1001.63
Radiometric thorium (scaled)	-1015.13
Radiometric total intensity (scaled)	-114.31
Radiometric uranium (scaled)	37.89



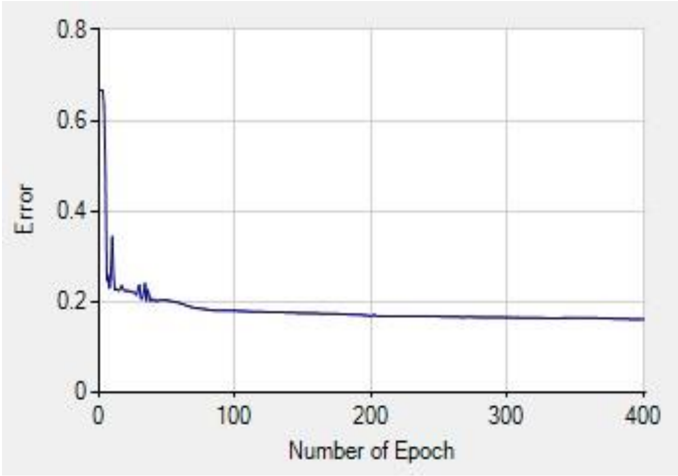
Mean Square Error (MSE)

Prediction Model #20



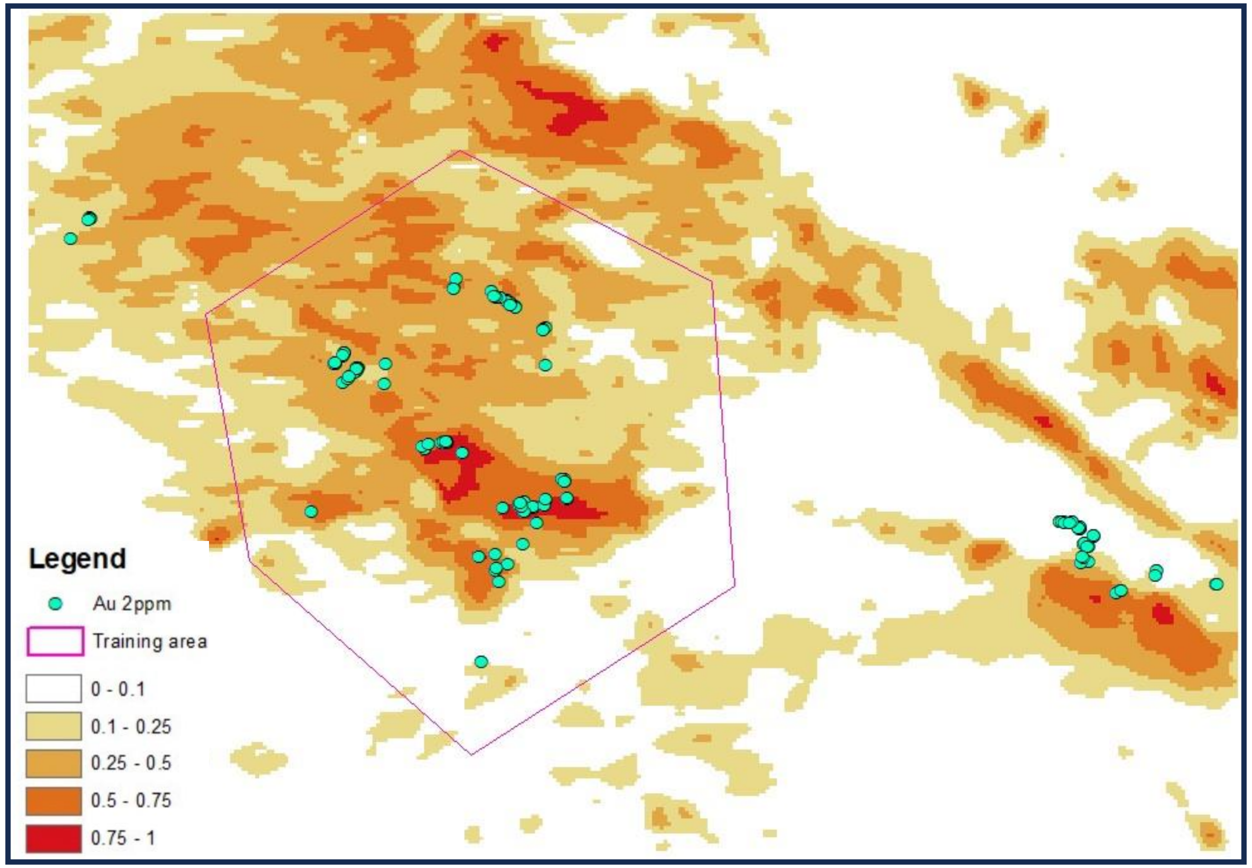
Model using GTK radiometric (U,Th,K and total) & Drone magnetic data

Name	Conn wgt
Radiometric potassium (scaled)	-62550.07
Radiometric thorium (scaled)	-885.11
Radiometric total intensity (scaled)	-399628.68
Radiometric uranium (scaled)	470.51
Drone Magnetics (scaled)	7604.46

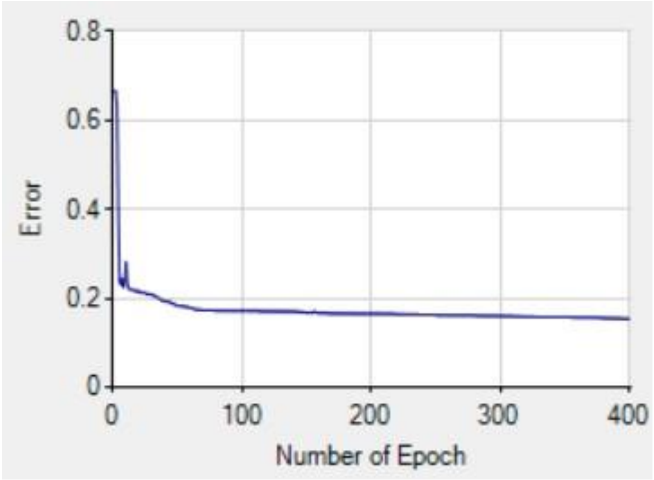


Mean Square Error (MSE)

Prediction Model #37



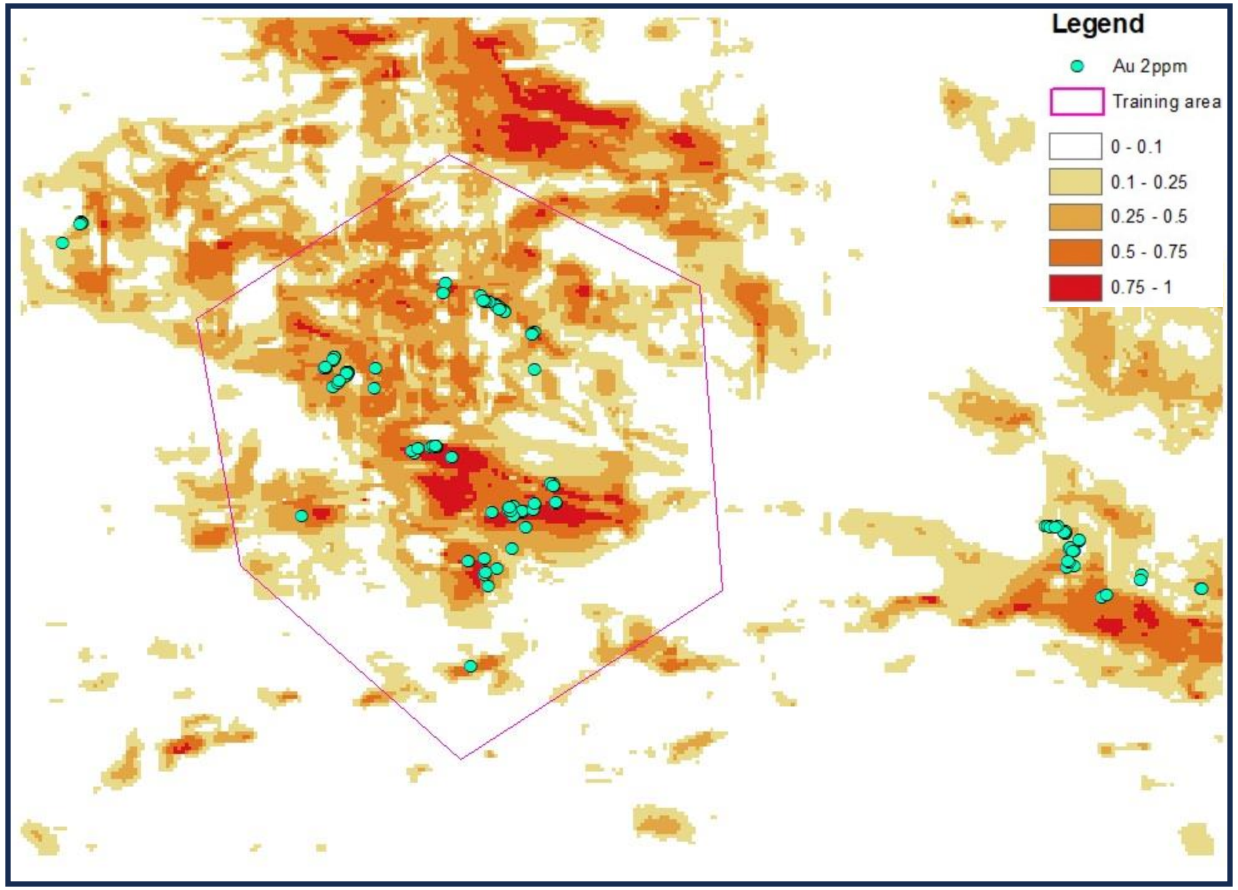
Name	Conn wgt
Radiometric potassium (scaled)	-2002.45
Radiometric thorium (scaled)	-976.54
Radiometric total intensity (scaled)	-2080.21
Radiometric uranium (scaled)	9.71
Basement resistivity (Rho2) (scaled)	-19.59
Apparent resistivity (Rhoa) (scaled)	-14.17
Drone Magnetics (scaled)	-1392.73



Mean Square Error (MSE)

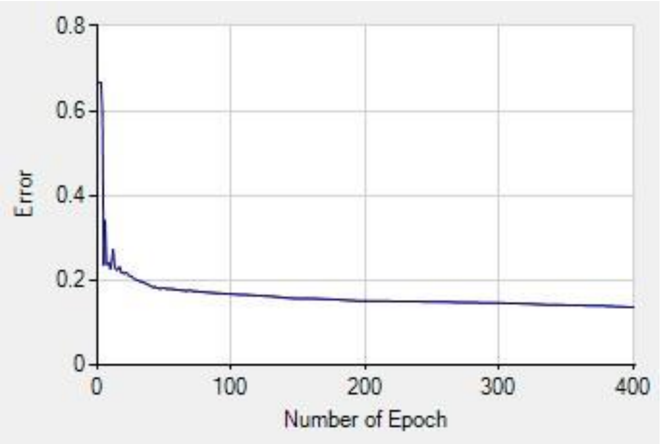
Model using GTK radiometric (U, Th, K and Total), resistivity and Drone magnetic data

Prediction Model #22



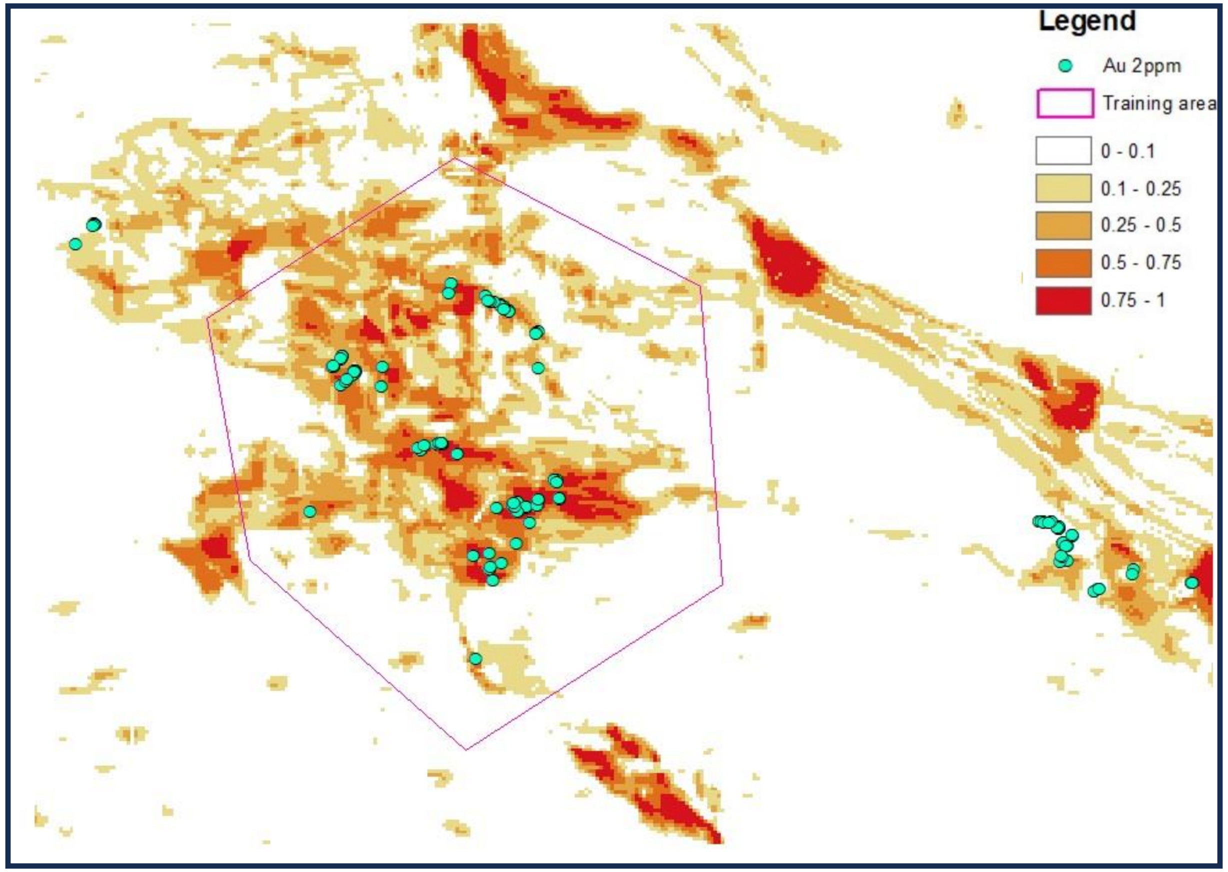
Model using GTK radiometric (U, Th, K and Total), resistivity, electromagnetic and Drone magnetics and it's derivatives data

Name	Conn wgt
Electromagnetic real (scaled)	-138.08
Radiometric potassium (scaled)	134.64
Radiometric thorium (scaled)	-72.33
Radiometric total intensity (scaled)	4.51
Radiometric uranium (scaled)	140.7
Basement resistivity (Rho2) (scaled)	14.81
Basement resistivity slope (Rho2) (scaled)	40135.88
Drone Magnetics (scaled)	653.11
Drone magnetics curvature negative (scaled)	-51.69
Drone magnetics curvature positive (scaled)	-38.17
Drone magnetics slope (scaled)	114.99



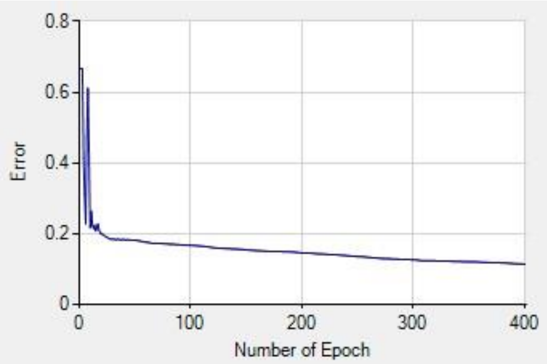
Mean Square Error (MSE)

Prediction Model #23



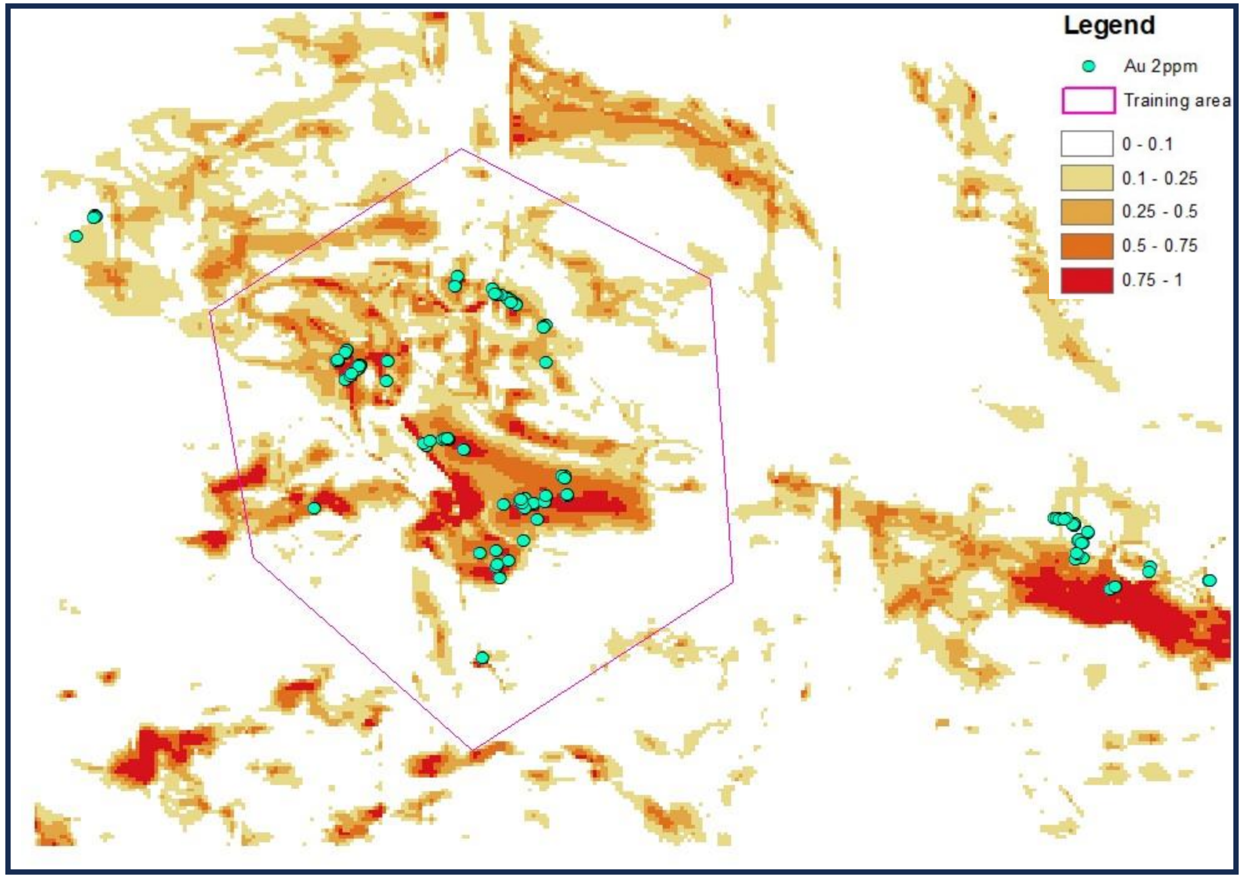
Model using GTK radiometric (U, Th, K and total), resistivity, electromagnetic, Drone magnetics and its derivatives and fault length of the area

Name	Conn wgt
Fault Lengths (Len 0 - 3.33 km)	157.85
Fault Lengths (Len 3.33 - 9.00 km)	-76.56
Electromagnetic real (scaled)	-221.77
Radiometric potassium (scaled)	-1107.46
Radiometric thorium (scaled)	-1319.8
Radiometric total intensity (scaled)	-4078.24
Radiometric uranium (scaled)	-149.63
Basement resistivity (Rho2 (scaled)	3.94
Basement resistivity (Rho2) Slope (scaled)	13576.07
Drone magnetics (scaled)	403.01
Drone magnetics curvature negative (scaled)	-39.54
Drone magnetics curvature positive (scaled)	-23.62
Drone magnetics slope (scaled)	-3303.62

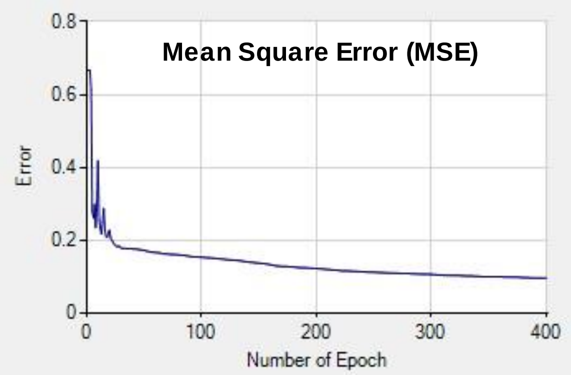


Mean Square Error (MSE)

Prediction Model #24

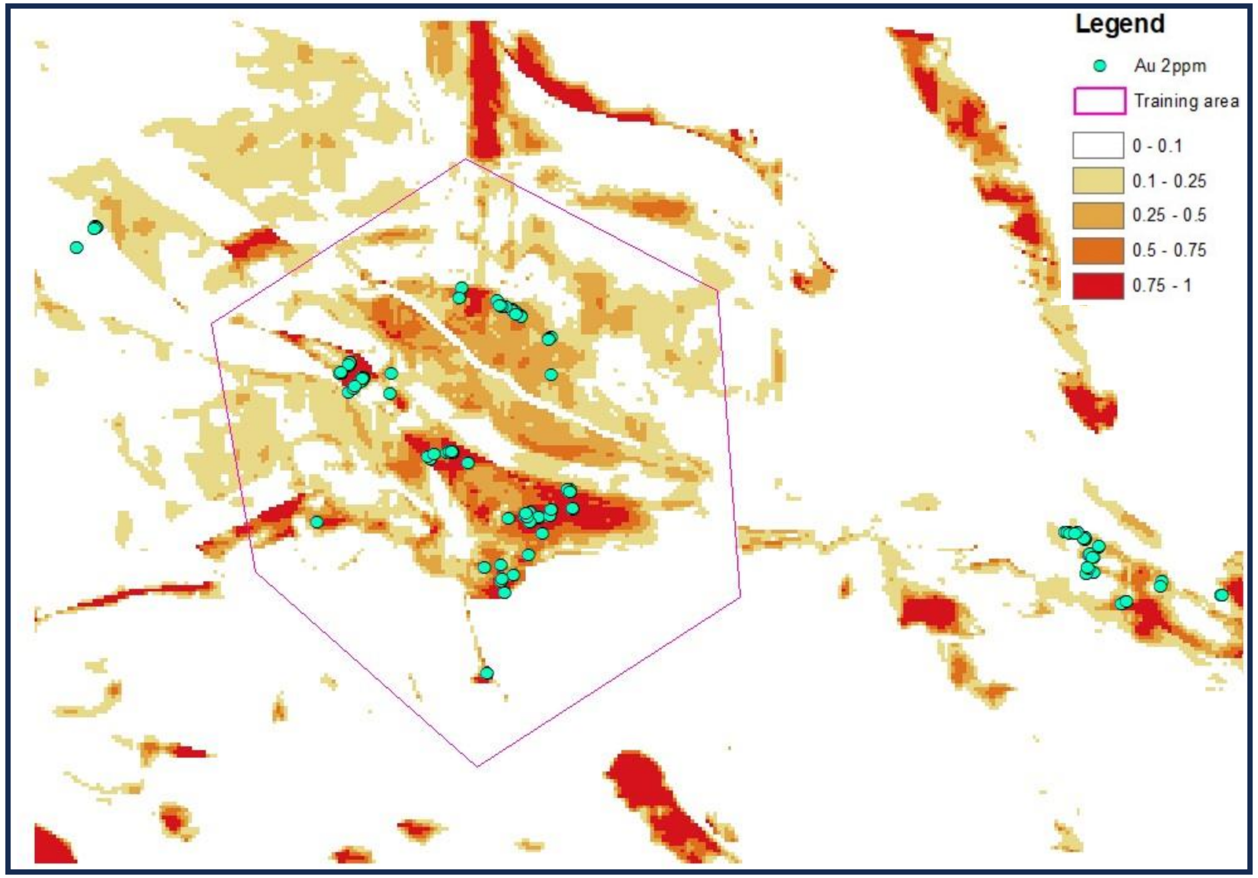


Name	Conn wgt
Faults Directions-(E_W direction)	4123.96
Faults Directions-(N_S direction)	3675.09
Fault Lengths (Len 0 - 3.33 km)	2216.32
Fault Lengths (Len 3.33 - 9.00 km)	222.97
Electromagnetic real (scaled)	-9.75
Radiometric potassium (scaled)	184.17
Radiometric thorium (scaled)	-60.09
Radiometric total intensity (scaled)	35.94
Radiometric uranium (scaled)	-51.07
Basement resistivity (Rho2) (scaled)	53.84
Basement resistivity (Rho2) Slope (scaled)	17508.62
Drone magnetics (scaled)	251.17
Drone magnetics curvature negative (scaled)	-41.11
Drone magnetics curvature positive (scaled)	-33.64
Drone magnetics slope (scaled)	142.16



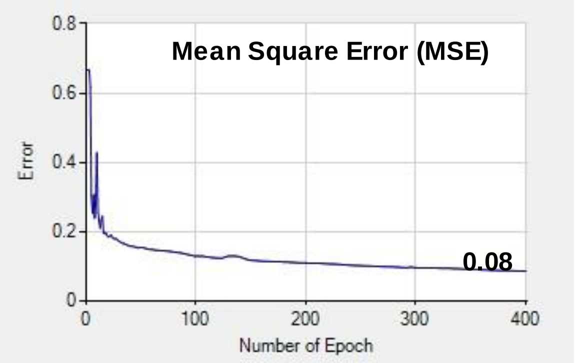
Model using GTK radiometric (U, Th, K and Total), resistivity, electromagnetic, Drone magnetics and its derivatives and fault length and direction of the area

Prediction Model #25

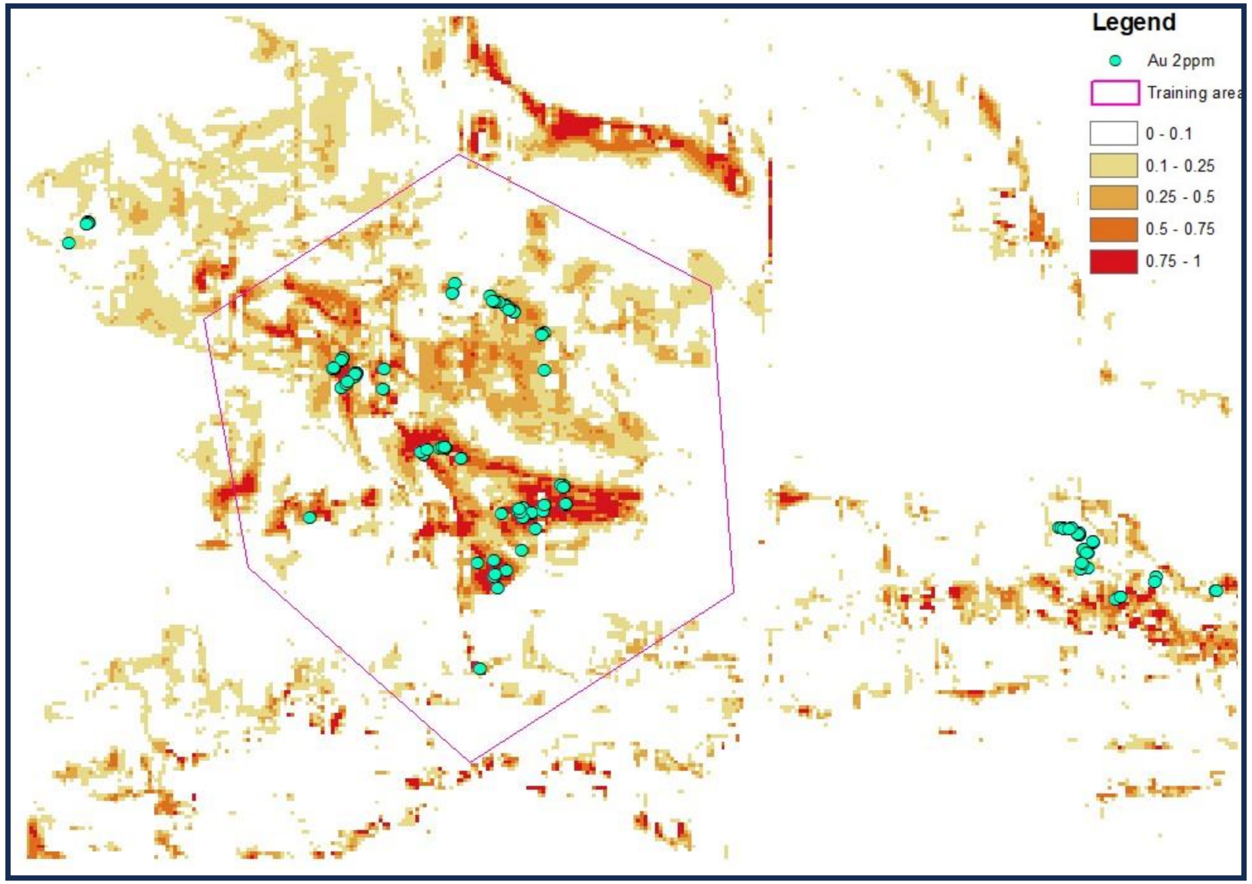


Model using GTK radiometric (U, Th, K and Total), resistivity, electromagnetic, Drone magnetics and its derivatives and fault length and direction with lithology of the area

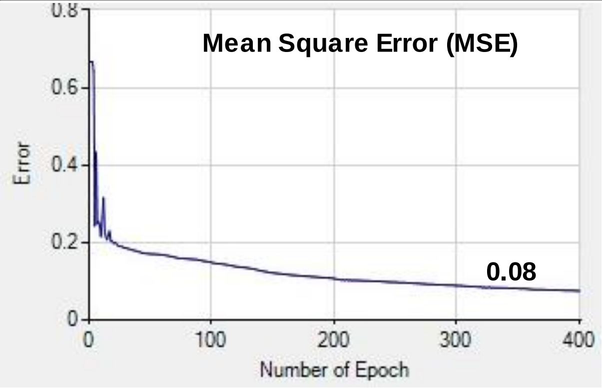
Name	Conn wgt
Faults Directions-(E_W direction)	7837.39
Faults Directions-(N_S direction)	26175.72
Area litology (Class SDST)	949.87
Fault Lengths (Len 0 - 3.33 km)	547.94
Fault Lengths (Len 3.33 - 9.00 km)	-156.21
Electromagnetic real (scaled)	-811.88
Radiometric potassium (scaled)	-369.77
Radiometric thorium (scaled)	-1457.57
Radiometric total intensity (scaled)	-229.54
Radiometric uranium (scaled)	-194.47
Basement resistivity (Rho2) (scaled)	-101.77
Basement resistivity (Rho2) Slope (scaled)	-10395.86
Drone magnetics (scaled)	-55.57
Drone magnetics curvature negative (scaled)	-179.04
Drone magnetics curvature positive (scaled)	-105.14
Drone magnetics slope (scaled)	-147.02



Prediction Model #35



Name	Conn wgt
Faults Directions- (E_W direction)	258.01
Faults Directions- (N_S direction)	169.09
Fault Lengths (Len 0 - 3.33 km)	68.99
Fault Lengths (Len 3.33 - 9.00 km)	172.12
Electromagnetic imag (scaled)	-478.53
Electromagnetic real (scaled)	-70.28
Radiometric total intensity (scaled)	209.77
Basement resistivity (Rho2 (scaled)	8.57
Basement resistivity (Rho2) curvature negative (scaled)	-82.73
Basement resistivity (Rho2) curvature positive (scaled)	743.94
Basement resistivity (Rho2) Slope (scaled)	23283.8
Drone magnetic 1VD (scaled)	-9.45
Drone magnetics (scaled)	252.21
Drone magnetics curvature negative (scaled)	-30.82
Drone magnetics curvature positive (scaled)	-0.41
Drone magnetics slope (scaled)	-17.78



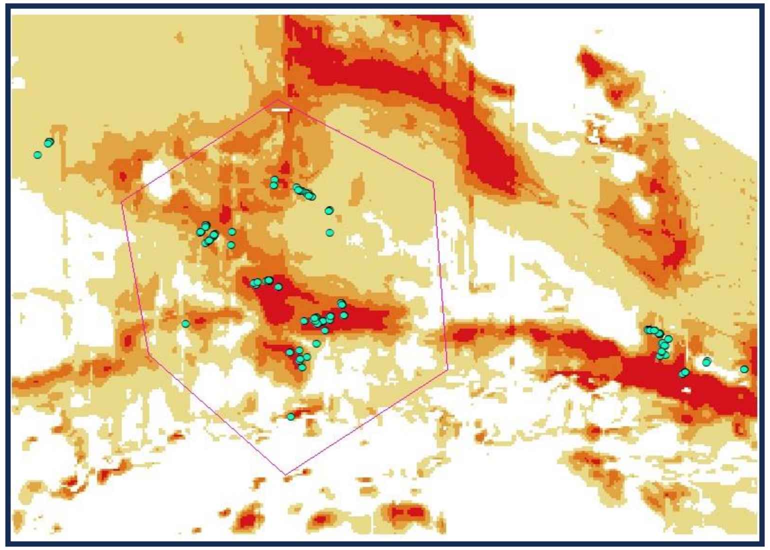
Model from GTK electromagnetic, radiometric (total), resistivity, Drone magnetics and its derivatives and fault length with fault direction

DroneSOM

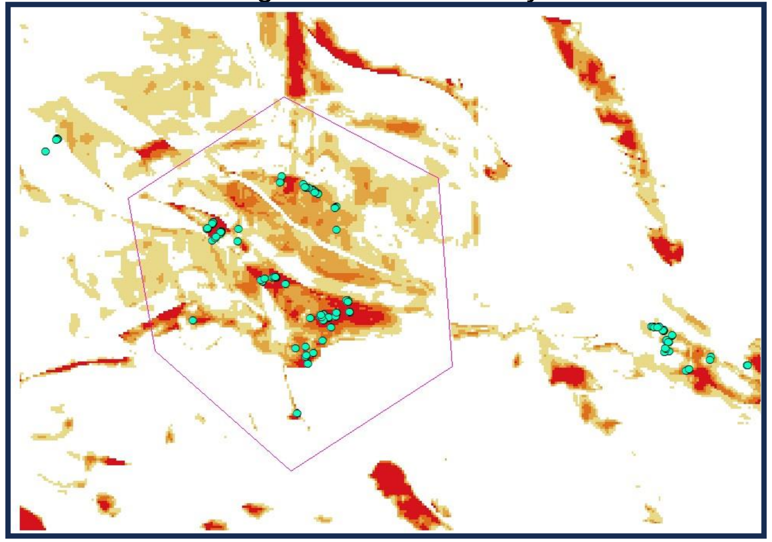
GTK radai DTU beak CONSULTANTS

Summary ANN prediction:

- ✓ Influence of the combination of the dataset used in the predictions
- ✓ The accuracy and resolution of the datasets (including geology)
- ✓ Importance of the chosen training area and the quality of the training dataset
- ✓ Consider the depth dependencies in different data sets ⇨ advangeo 3D
- ✓ Predictive mapping is one of the most efficient working tools for greenfield exploration



Parameters-Magnetic and resistivity data



Parameters-Magnetic, EM, radiometric, resistivity, tectonic and lithology data

Supported by

eit RawMaterials Connecting matters

Co-funded by the European Union

4) SOM analysis using GisSOM software

Supported by

Connecting matters

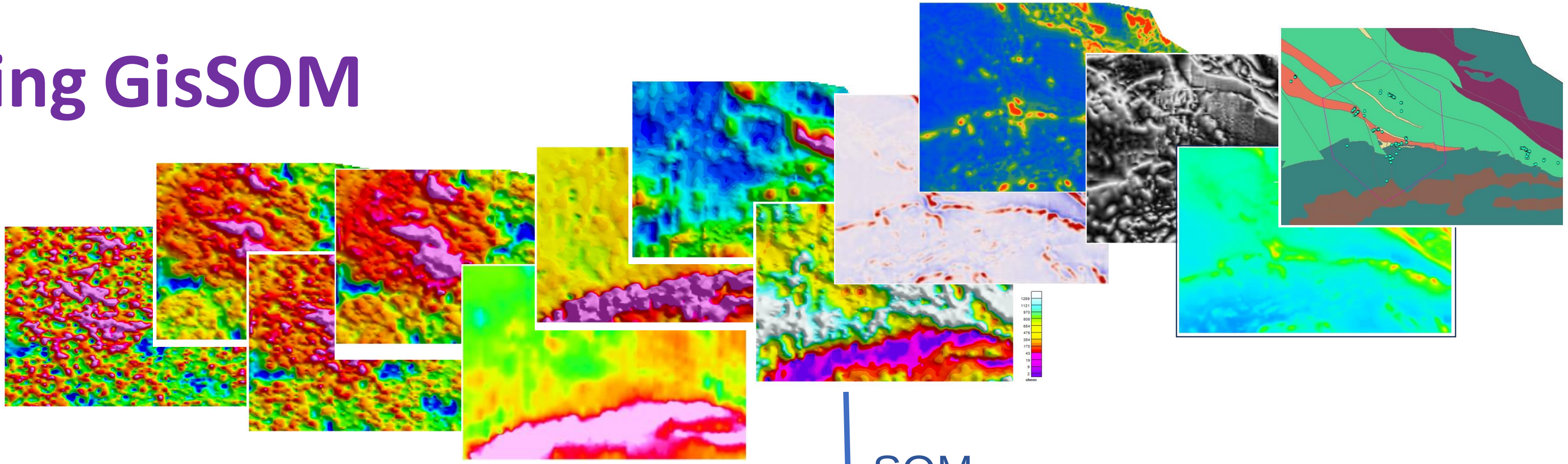
Co-funded by the European Union

DroneSOM

SOM analysis using GisSOM

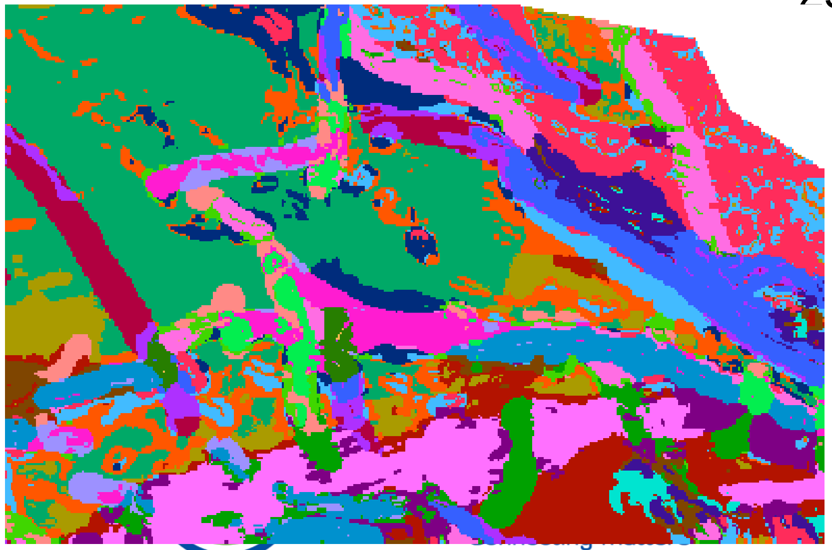
Dataset for the ANN result #35

Name	Conn wgt
Faults Directions (Class E_W)	258.01
Faults Directions (Class N_S)	169.09
Fault Lengths (Len 0 - 3.33 km)	68.99
Fault Lengths (Len 3.33-9.00 km)	172.12
Electromagnetic imag (scaled)	-478.53
Electromagnetic real (scaled)	-70.28
Radiometric Total Intensity (scaled)	209.77
Basement Resistivity (scaled)	8.57
Basement Resistivity - curvature negative (scaled)	-82.73
Basement Resistivity - curvature positive (scaled)	743.94
Basement Resistivity - Slope (scaled)	23283.8
Drone Magnetic 1VD (scaled)	-9.45
Drone Magnetics (scaled)	252.21
Drone Magnetics Curvature negative (scaled)	-30.82
Drone Magnetics Curvature positive (scaled)	-0.41
Drone Magnetics Slope (scaled)	-17.78

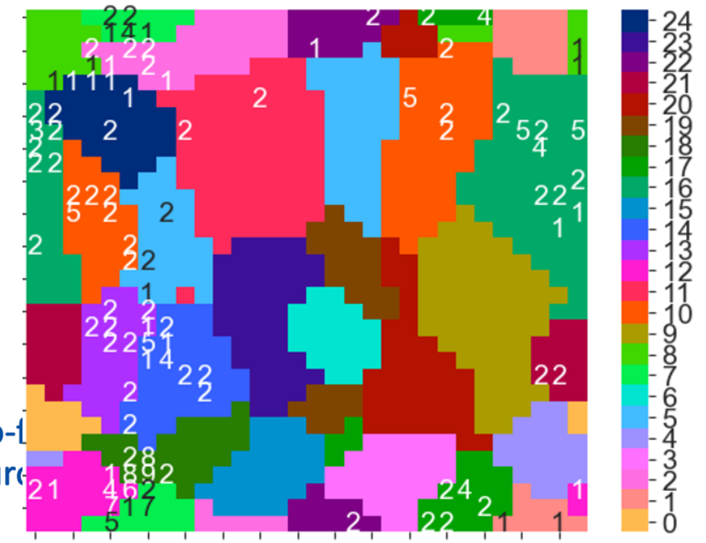


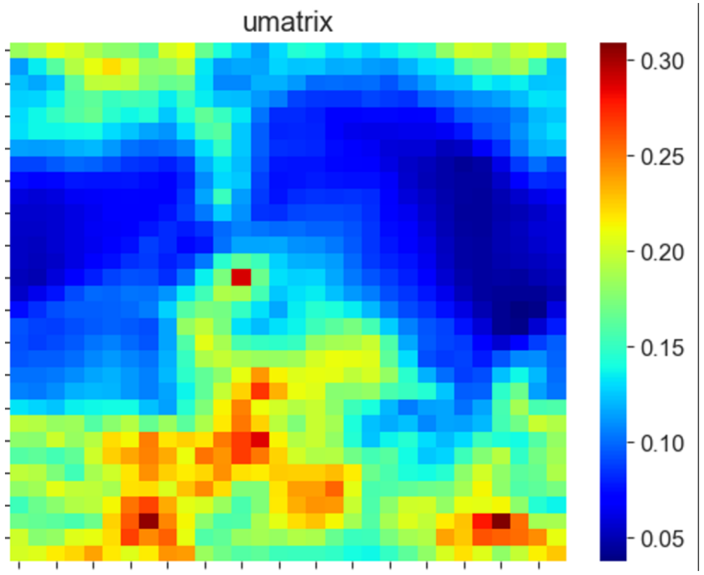
SOM
K-means

25 clusters



To
geospace



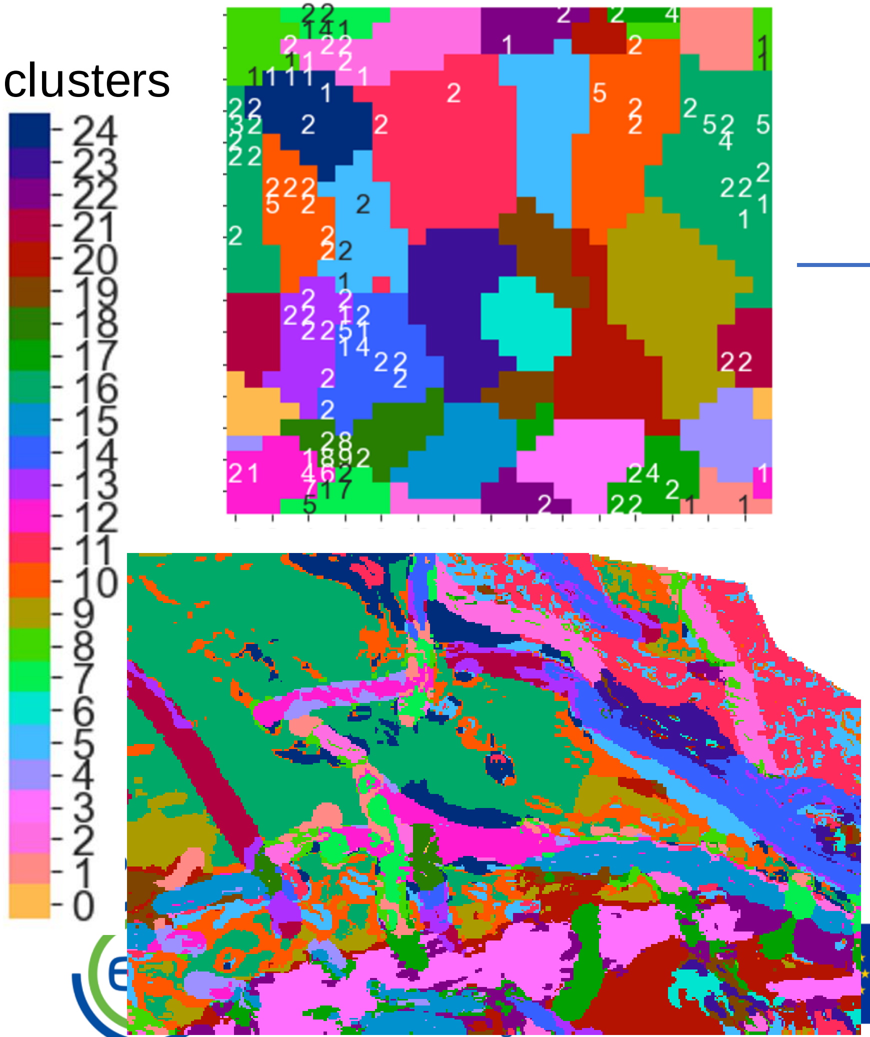


Co-f
Eur

DroneSOM

SOM analysis using GisSOM

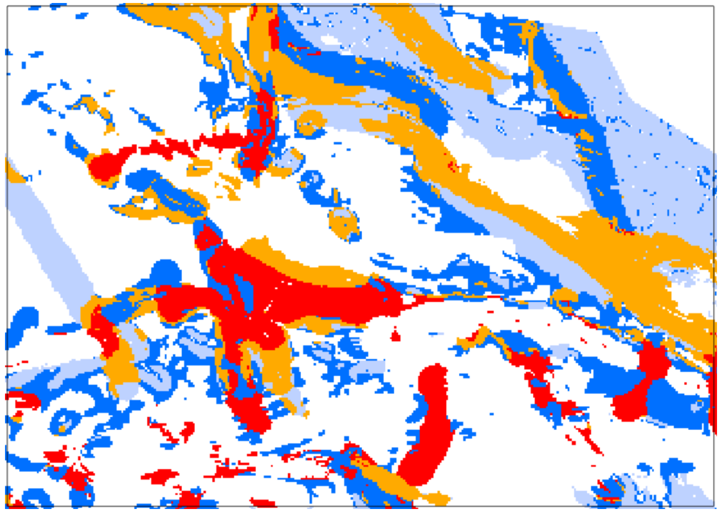
25 clusters



Cluster	Ncells_with_Au/ Ncells_tot
0	0.000000e+00
1	7.406036e-04
2	8.361204e-04
3	0.000000e+00
4	0.000000e+00
5	2.011971e-04
6	0.000000e+00
7	4.353234e-03
8	1.283285e-03
9	0.000000e+00
10	5.314061e-04
11	8.173273e-05
12	9.005236e-03
13	1.298327e-03
14	1.191895e-03
15	0.000000e+00
16	7.067138e-04
17	2.265598e-03
18	5.136986e-03
19	0.000000e+00
20	0.000000e+00
21	2.255554e-04
22	8.303924e-04
23	0.000000e+00
24	1.107910e-03

High prospectivity classes based on known sites with elevated gold concentration.

- Highest
- High

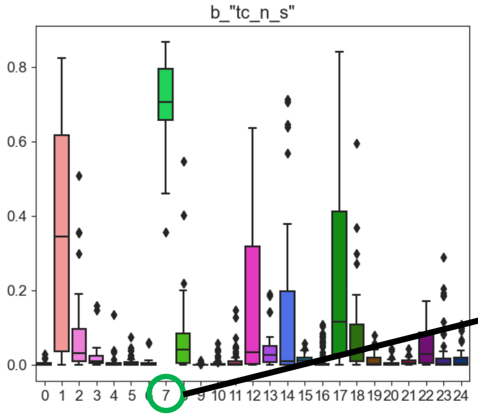


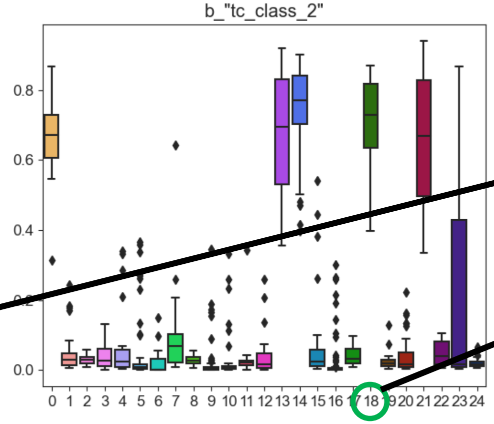
Co-funded by the European Union

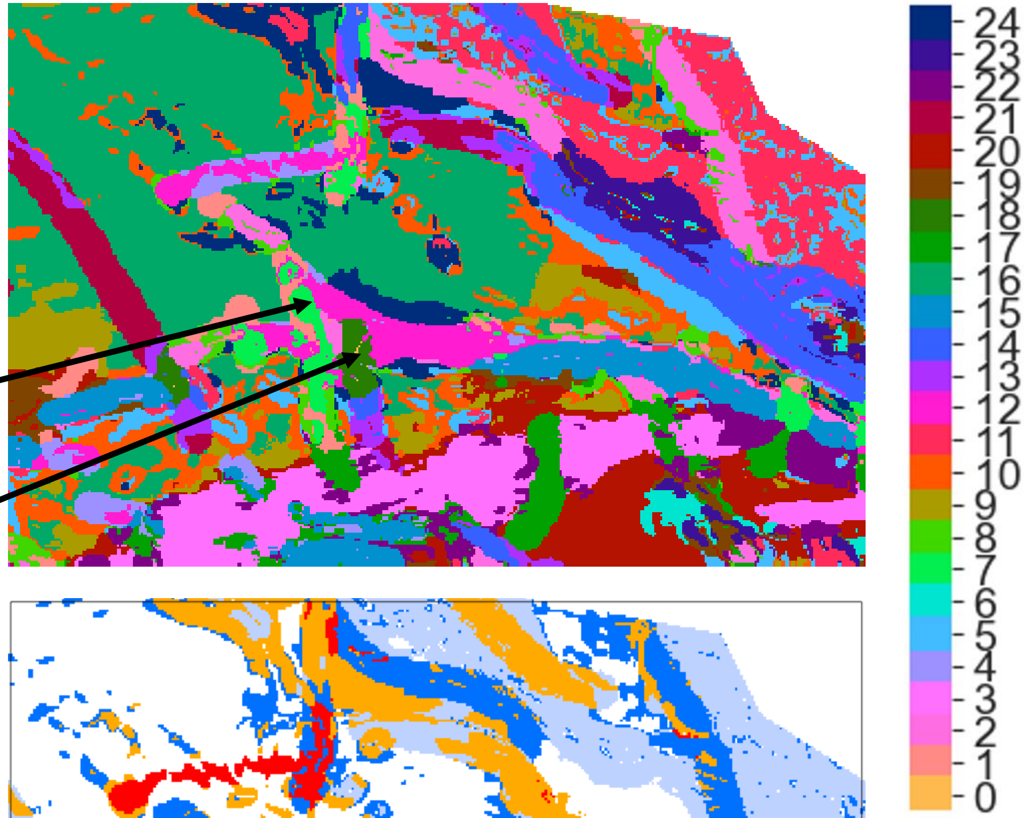
DroneSOM

SOM analysis using GisSOM

Distribution of input features in prospective clusters

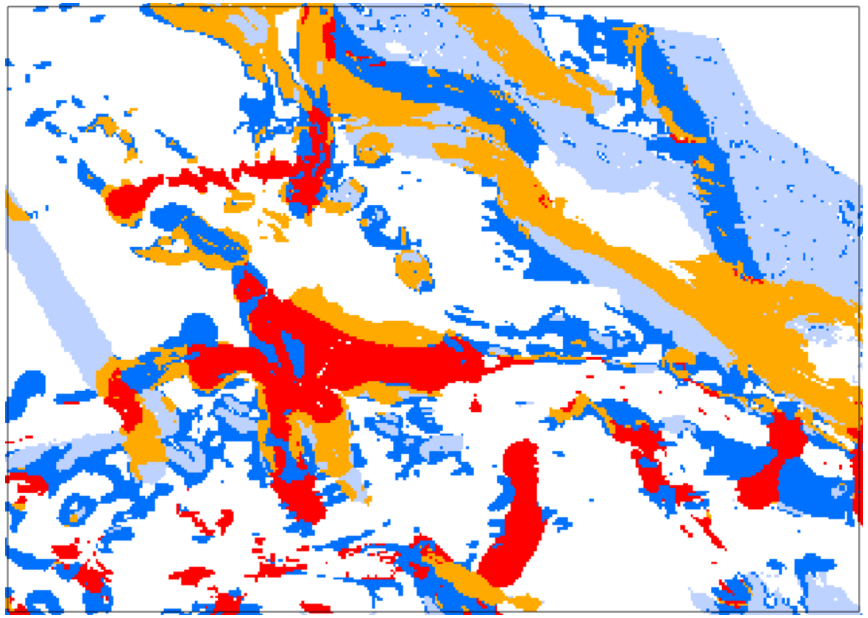






High prospectivity classes based on known sites with elevated gold concentration.

- Highest
- High



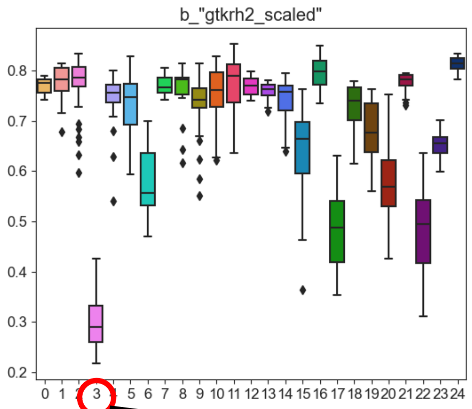
Supported by

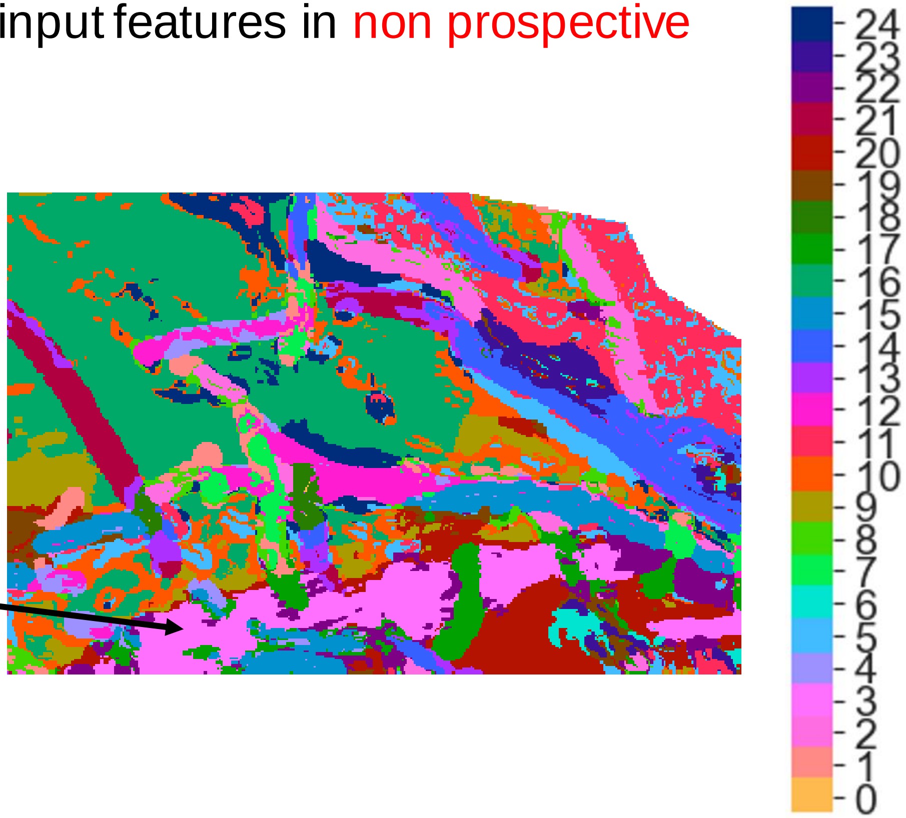
EIT RawMaterials Connecting matters

Co-funded by the European Union

SOM analysis using GisSOM

Distribution of some input features in non prospective clusters

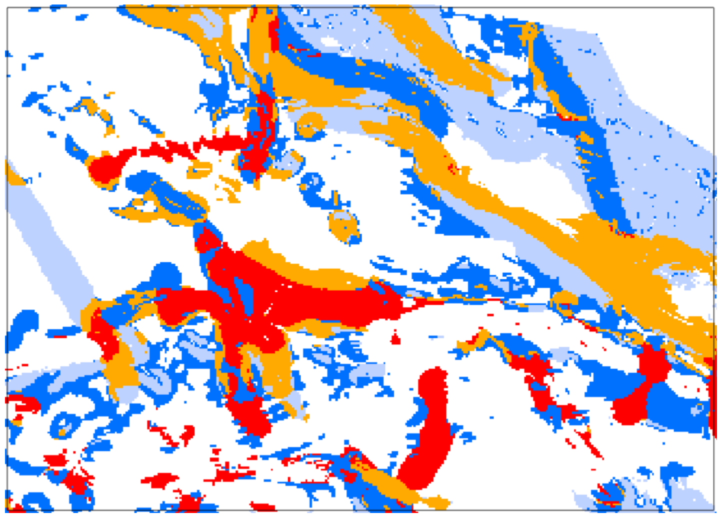




High prospectivity classes based on the occurrence of known elevated gold concentrations in clusters

Highest

High



Supported by
eit RawMaterials
Connecting matters
Co-funded by the European Union

Comparison of ANN and SOM results

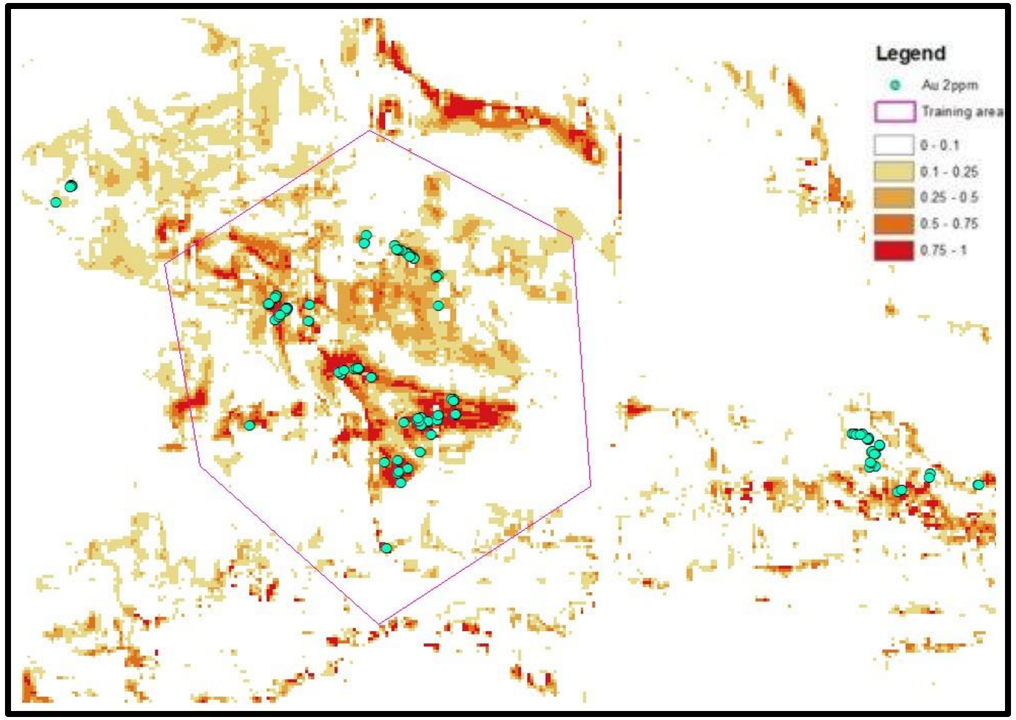
Supported by

Connecting matters

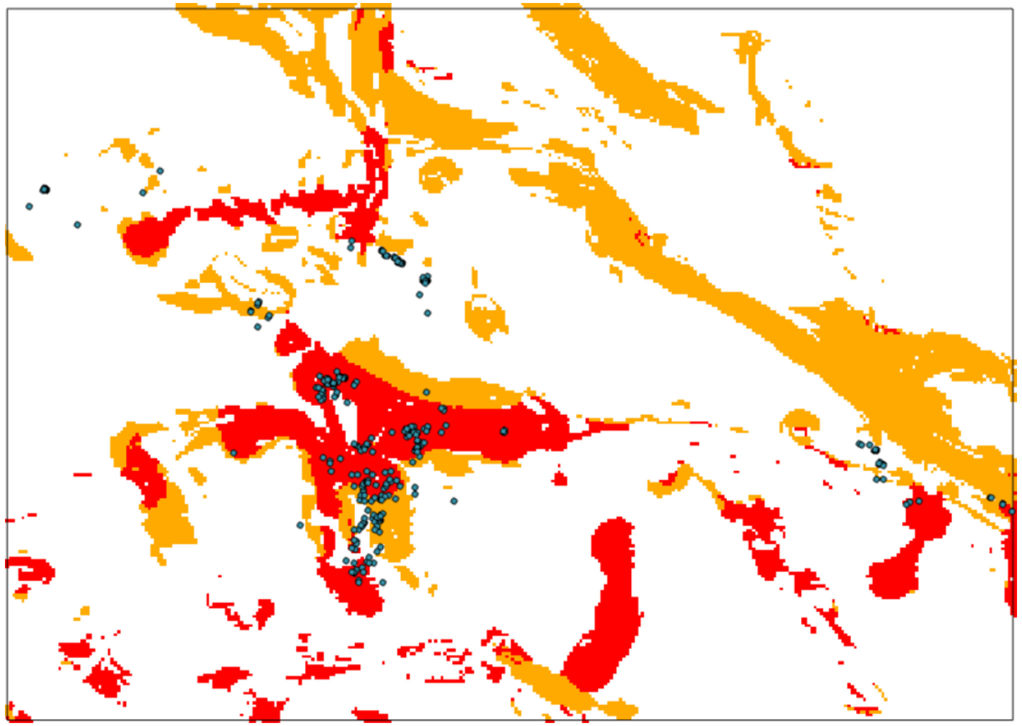
Co-funded by the European Union

Comparison of ANN and SOM results

ANN prediction result



SOM K-means clustering result



Supported by

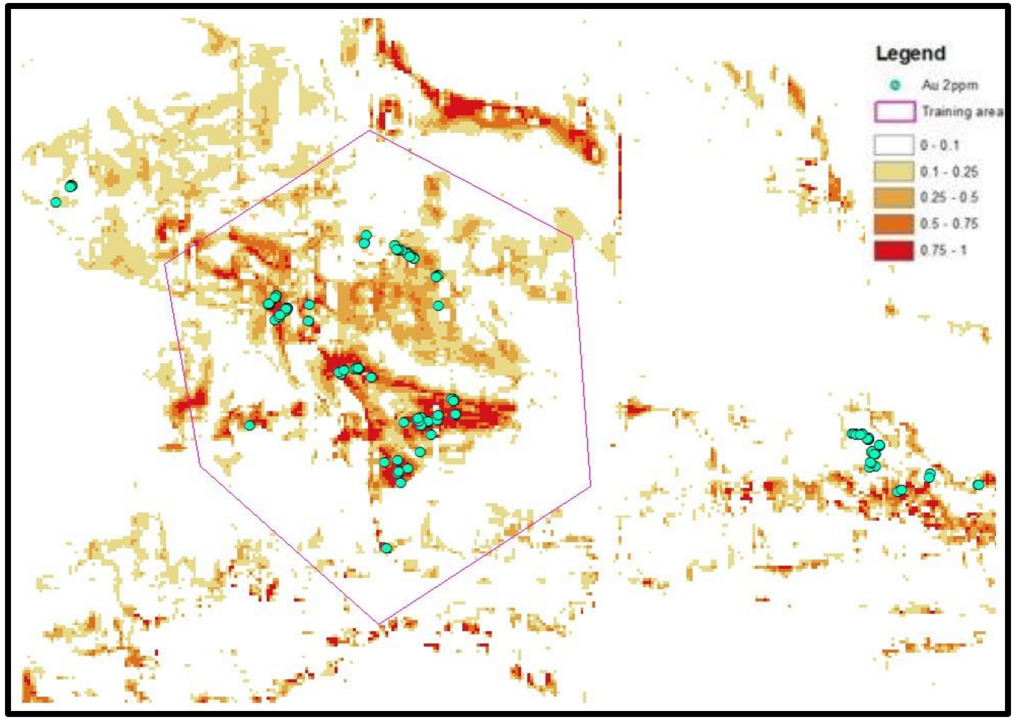
Co-funded by the European Union

DroneSOM

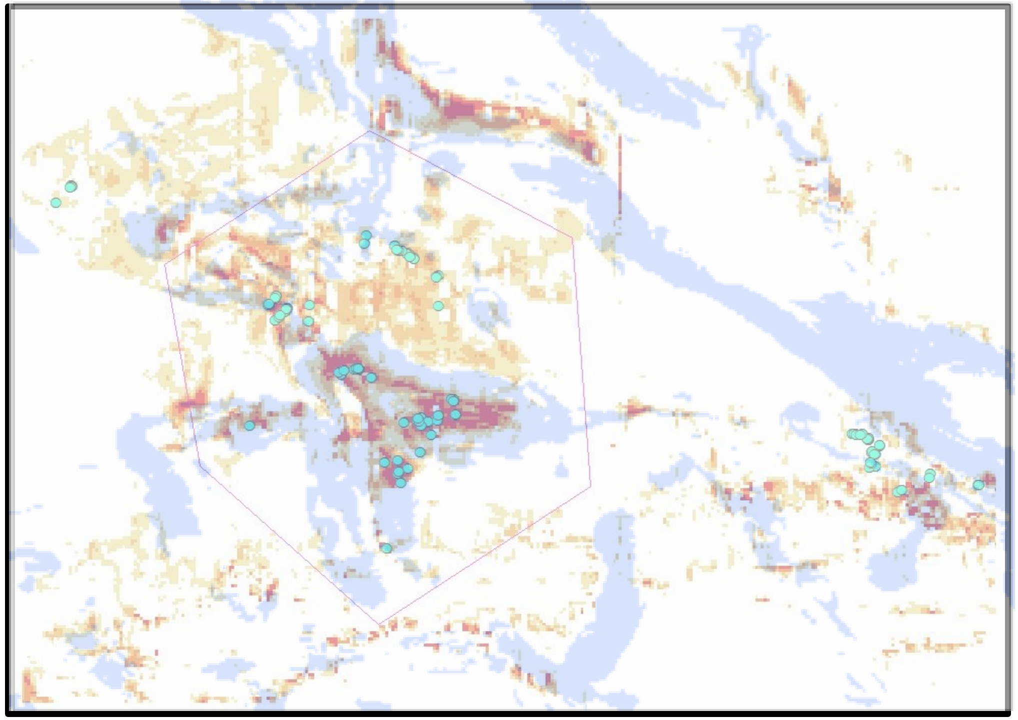
GTK radai DTU beak CONSULTANTS

Comparison of ANN and SOM results

ANN prediction result



SOM K-means clustering result



Supported by

eit RawMaterials Connecting matters

Co-funded by the European Union

DroneSOM

GTK radai DTU beak CONSULTANTS

5) Work procedure/Business Collaboration

Supported by

eit RawMaterials Connecting matters

Co-funded by the European Union

Work procedure

Prospectivity mapping could work efficiently for new Exploration License area.

- Neural Networks can be trained in nearby known areas that have good training data available
- Trained Network can then be applied to new exploration area
- Prepare preliminary prospectivity map, compare with known occurrences, if any
- Focus field work on potential areas in the early phase of exploration
- Iterative work, repeat training and modelling with additional field (=training) data and geological/geophysical/geochemical information once available

Supported by

RawMaterials
Connecting matters

Co-funded by the
European Union

DroneSOM

GTK radai DTU beak CONSULTANTS

Work procedure

Investigation of the area

Regional geology, mineral systems, and exploration potential of your target area.

Geodatabase of the area

Geological maps
Structural maps
Remote sensing data
Geophysical data
Geochemical data

Additional Information

Knowledge and understanding of input data

Data Integration and Processi ng

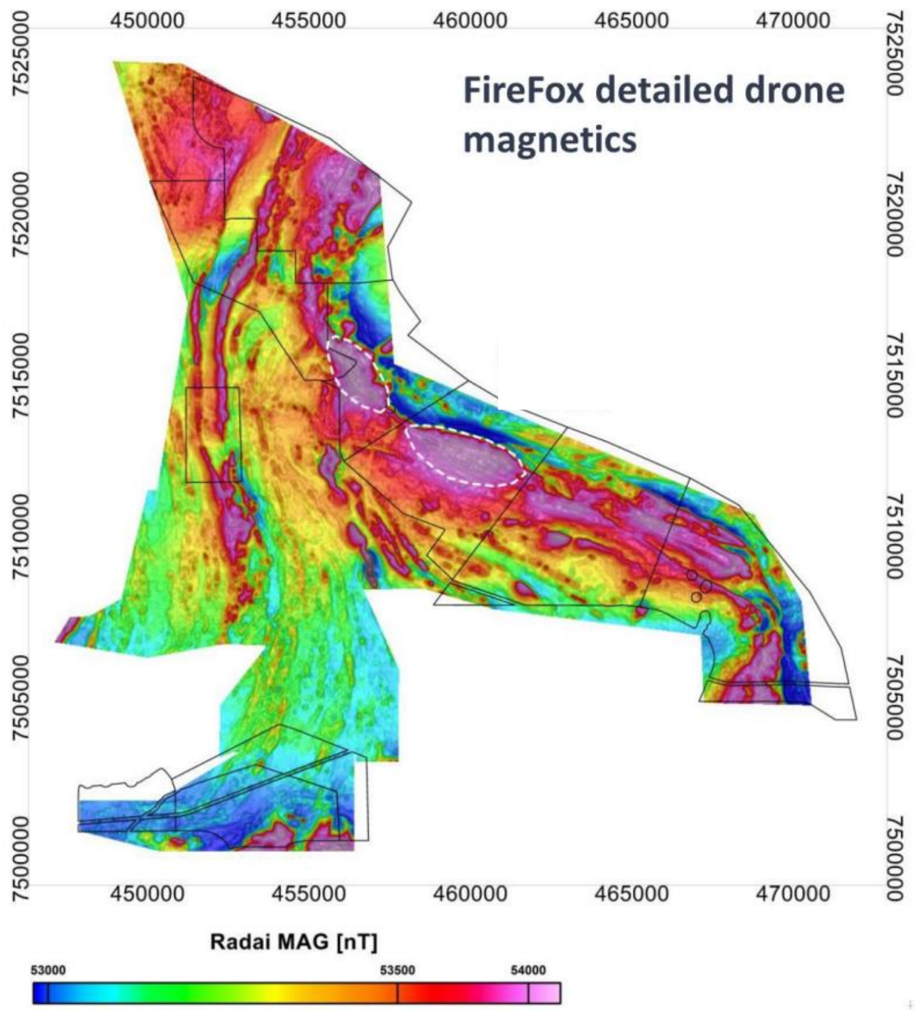
Define Training Scenario

Generate prospectivity maps and analyse

Change parameters
Improve prediction

Case study: Firefox gold Corp.

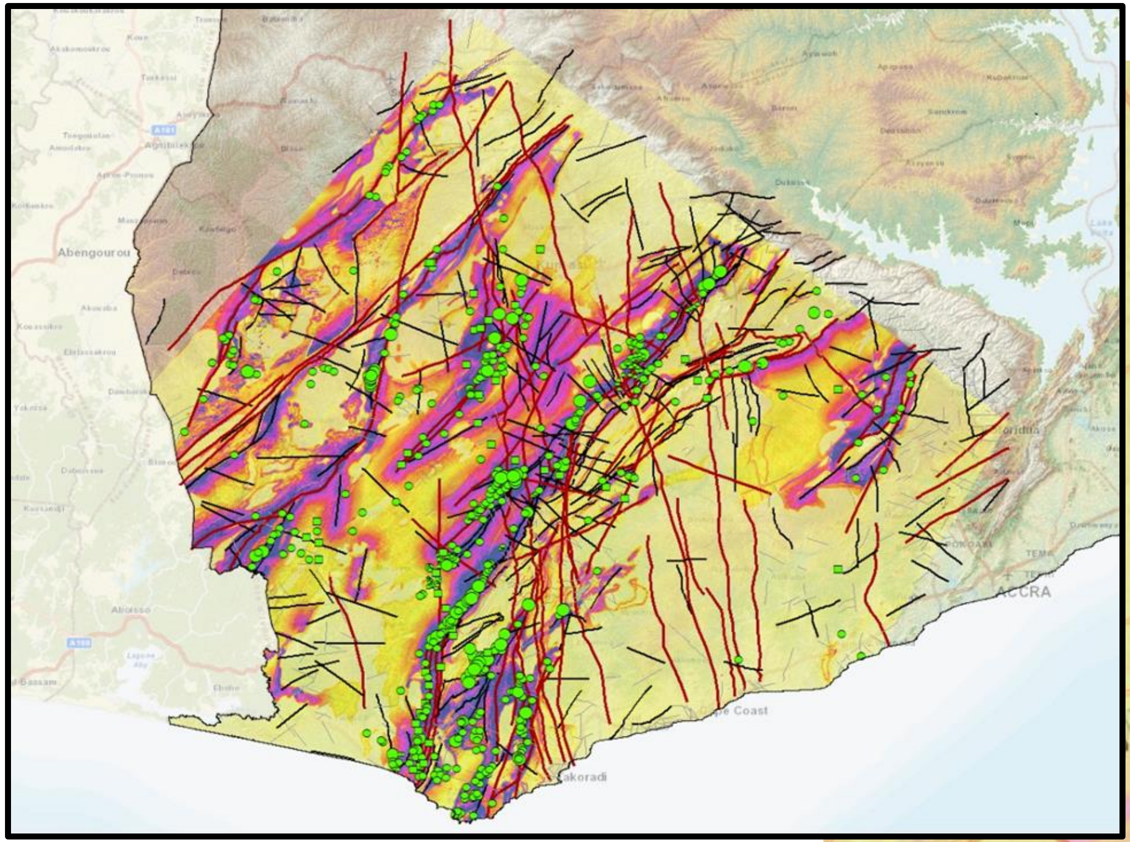
- Situated in the Lapland, Finland
- Available regional geology data /historical data
- Available geophysical, geological and or geochemical data
- High precision drone magnetic data
- Ongoing study for mineral prospectivity mapping

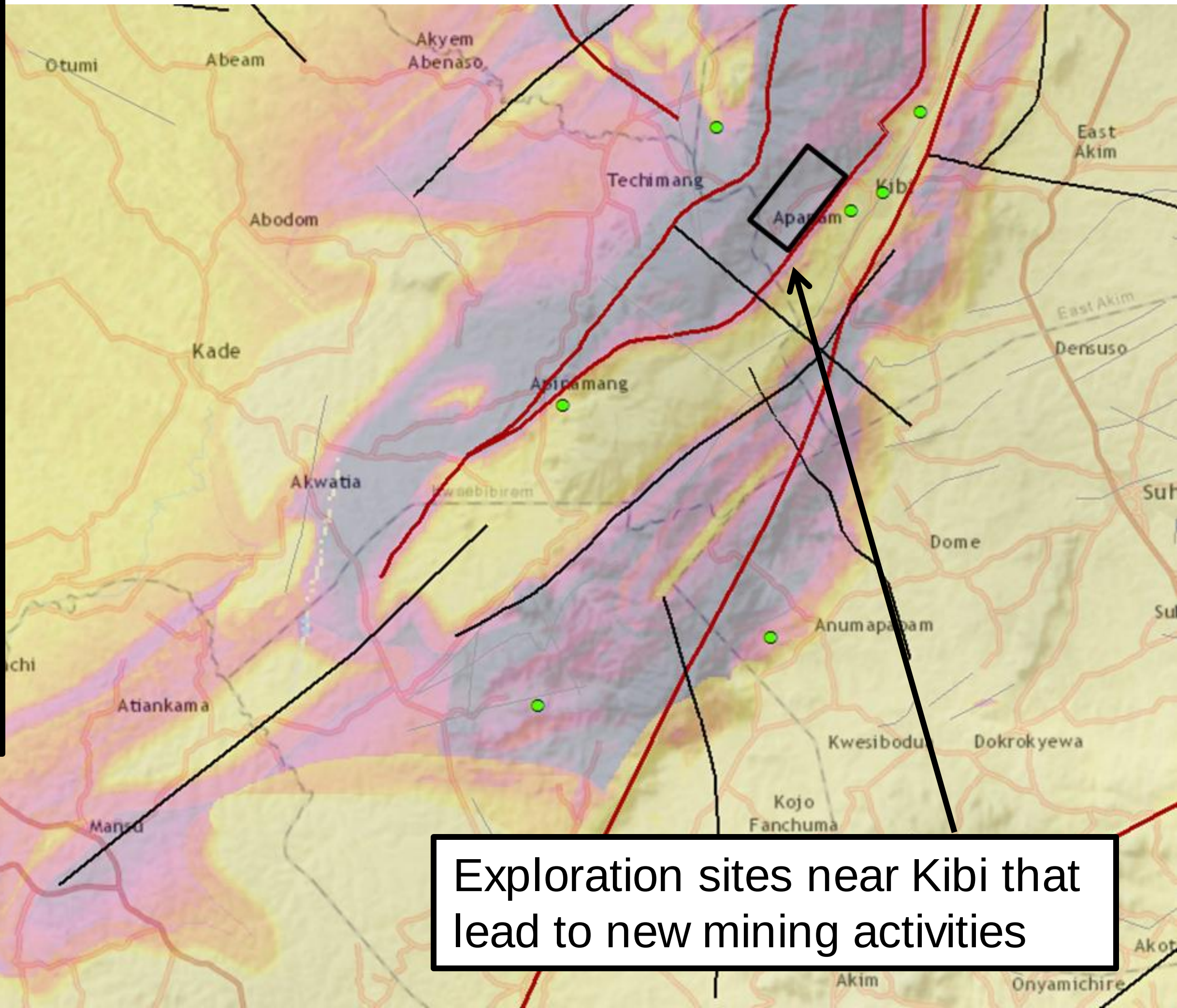


(https://www.firefoxgold.com/images/Presentation/2023/Firefox_Gold_Presentation.pdf)

Supported by
RawMaterials
Connecting matters
Co-funded by the European Union

Case study: Gold Deposits in SW Ghana (by Beak)





Supported by

Input Data
Stuctural data
Large fault legth & direction
Small fault length & direction
Striking direction 5-75 degree
Junctions
Lithology
Magnetic absolute, slope and aspect

DroneSOM

GTK radai DTU beak CONSULTANTS

Supported by

eit RawMaterials Connecting matters

Co-funded by the European Union

DroneSOM

GTK radai DTU beak CONSULTANTS

Feedback:

Dr. Juhani Ojala, Chief geologist from Aurion Resources:

"DroneSOM is developing mineral exploration methods by harnessing drones and machine learning, aiming for efficient and cost-effective geophysical survey tools. Emphasizing continuous innovation and development, the project underscores the critical importance of advancing and refining exploration techniques for successful exploration."

Mr. Mikko Nenonen , Exploration Manager from FireFox Gold Corp.

"DroneSOM's innovative approach, integrating geological parameters, regional geophysical data, and detailed magnetic drone surveys with advanced ANN predictive modeling and SOM technology, has demonstrated remarkable success in identifying promising and potentially mineralized areas. A groundbreaking project at the forefront of mineral exploration."

Supported by

eit RawMaterials Connecting matters

Co-funded by the European Union