Batter metal exploration: Integrating satellite, airborne, drone and field-data with machine learning outputs in Cornwall

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Summary

The geothermal brines associated with granitic rocks in Cornwall have been proven to have globally significant lithium grades. These hot-brines are often localized along faults and fractures and alter the surrounding country rocks.

The clay and iron minerals associated with hydrothermal alteration have characteristic spectral signatures that can be identified by satellites. Multispectral and hyperspectral satellites were used to map the alteration and generate target areas for fieldwork. High spatial and spectral resolution airborne hyperspectral data and 3D drone imagery were also integrated to enable more precise target detection. Fieldwork follow-up with a field-spectrometer confirmed the presence of alteration.

Combined with the spectral mapping, satellite elevation data sets and airborne LiDAR were used to generate semi-automated fault mapping workflow. Machine learning algorithms and automated workflows resulted in the rapid processing, interpretation, and delineation of possible faulted areas. The outputs from these were integrated with the mineral alteration mapping to geologically contextualize the target areas.

Using these targets, geologists from Cornish Lithium undertook a ground validation campaign as a key element of the iterative approach that the machine learning model took. This allowed for a highly accurate prospectively map to be generated and the improved delineation of field target areas.

Introduction

The World Bank (Hund et al. 2020) suggests that the demand for battery metals is predicted to rise above five times the current supply levels by 2050. This, combined with the energy transition towards reduced emissions, has led to increased exploration for battery metals such as lithium, cobalt, nickel, and copper.
The geothermal brines associated with granitic rocks in Cornwall have been proven to have globally significant lithium grades (Cornish Lithium 2020). These hot-brines are often localized along faults and fractures and alter the surrounding country rocks. This project aimed to map these fault zones with a suite of remote platforms.

Methodology

The clays and iron minerals associated with the hydrothermal alteration often have identifiable spectral signatures that can be mapped by satellites (van der Meer et al. 2014). Multispectral satellites (Landsat-8, Sentinel-2, WorldView-3) and the new hyperspectral satellite PRISMA were used to map the alteration and generate target areas for fieldwork. The integration of high spatial and spectral resolution airborne hyperspectral and 3D drone imagery enabled further target delineation (Figure 1).

Figure 1 - *From left-to right; Airborne hyperspectral imagery showing the NNW-SSE trending vein, the clay alteration signature associated with the vein is shown in yellow on the central image and the 3D drone mapping of the vein is shown to the right.*

Fieldwork follow-up with a field-spectrometer resulted in confirmation of the altered country rocks (Figure 2).

Figure 2 - *From left-to right; Clay alteration area identified from the Worldview-3 image shown in red and from the airborne hyperspectral shown in yellow, the inset shows Cornish Lithium geologists taking field samples. The central image shows the locational accuracy of the mapping and the photograph to the right the samples taken and sent off for spectral analysis.*

Combined with the spectral mapping satellite elevation data sets (AW-3D, SRTM) and airborne LiDAR were used to generate semi-automated fault mapping workflow (Aghaee Rad 2019 & Gallwey et al. 2020). Machine learning algorithms and automated workflows resulted in the rapid processing, interpretation, and delineation of possible faulted areas (Figure 3). The outputs of which were then integrated with the mineral alteration mapping to geologically contextualize the target areas; mapping areas of correlation and further delineate field-targets.

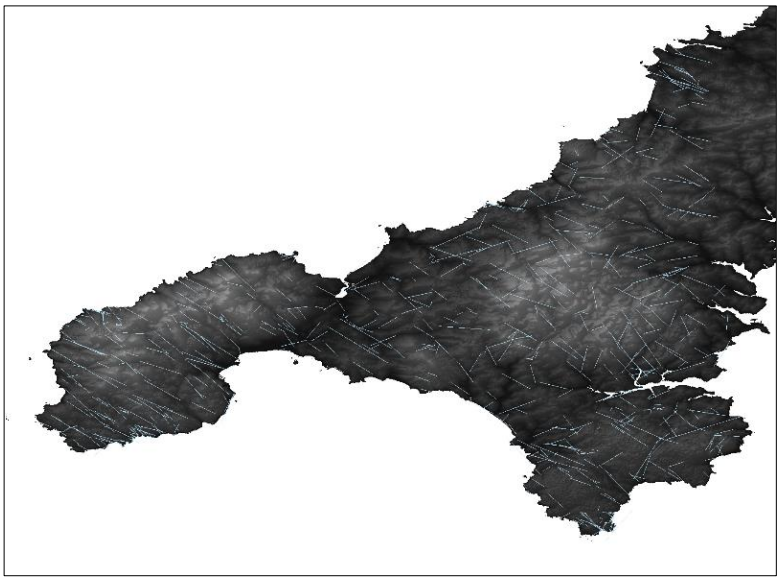

Figure 3 - *Machine learning output using the LiDAR*

Conclusions

Using these targets, geologists from Cornish Lithium undertook a ground validation campaign as a key element of the iterative approach that the machine learning model took. This allowed for a highly accurate prospectively map (Figure 4) to be generated and the improved delineation of field target areas.

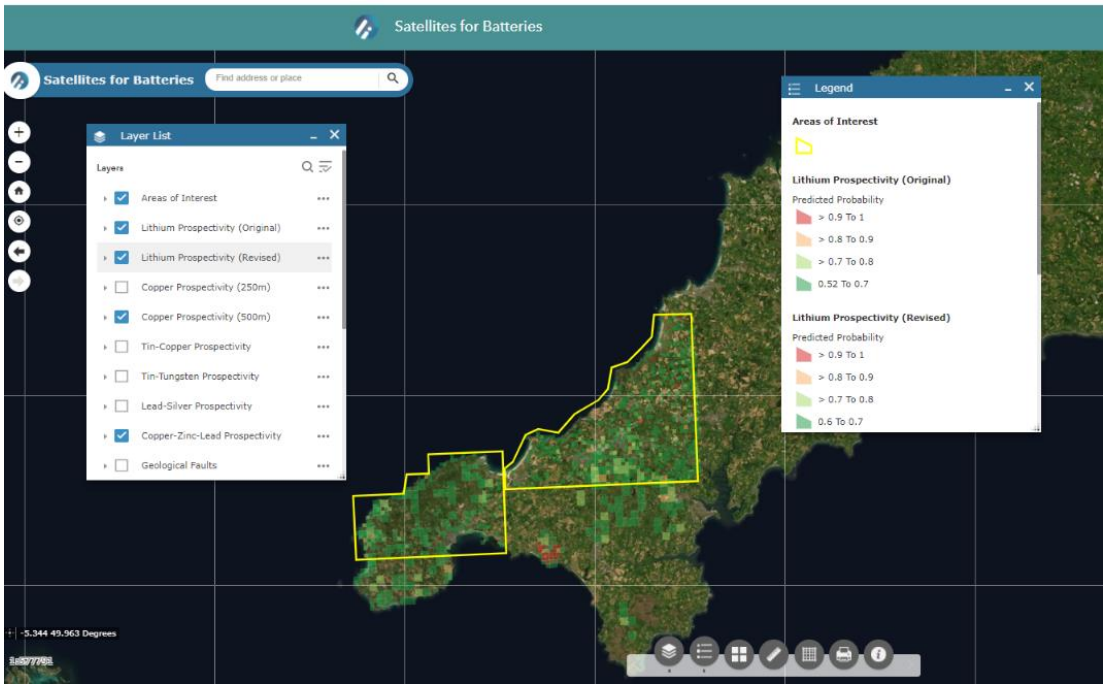

Figure 4 – *Lithium prospectively map and tool generated from the project.*

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References

Aghaee Rad, M. A. [2019] Machine learning of lineaments from magnetic, gravity and elevation maps. University of British Columbia. DOI: 10.14288/1.0376558.

Cornish Lithium, 2020: Company update. https://cornishlithium.com/company-announcements/cornish-lithium-releases-globally-significant-lithium-grades/

Gallwey, J., Yeomans, C., Tonkins, M., Coggan, J., Vogt, D., Eyr, M. [2020] Using deep learning and Hough transformations to infer mineralised veins from LiDAR data over historic mining areas. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLIII-B2-2020.

Hund, K., La Porta, D., Fabregas, T. P., Laing, T., Drexhage, J. [2020] Minerals for Climate Action: The Mineral Intensity of the Clean Energy Transition. International Bank for Reconstruction and Development/The World Bank.

van der Meer, F.D., van der Werff, H.M.A., van Ruitenbeek, F.J.A., Hecker, C.A., Bakker, W.H., Noomen, M.F., van der Meijde, M., Carranza, E.J.M., Boudewijn de Smeth, J., Woldai, T. [2014] Multi- and hyperspectral geologic remote sensing: A review. International Journal of Applied Earth Observation and Geoinformation 14.1, pp. 112-128.