Methods, Models, and Movement: Examining Multiple Trace Element Dataset to Explore Past Land-Use Dynamics

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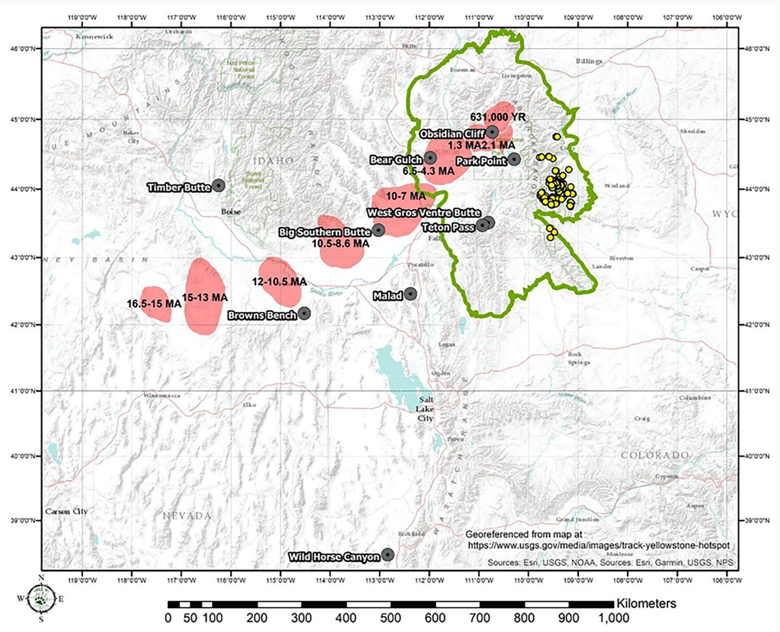
The GRSLE Project

To date, the GRSLE Project has recorded >11,000 obsidian artifacts in the Greater Yellowstone ecosystem. Of these, >1,400 have been sourced with Elemental X-Ray Fluorescence (EXRF) technology. One of the tenants of the GRSLE Project has been to practice "catch and release" archaeological recording where >99.9% of recorded artifacts are left in place. Obsidian sourcing is among the few data sources that requires removal of artifacts. By developing and testing sourcing accuracy using portable XRF (pXRF) data we may accurately source obsidian artifacts in the field and continue to minimize our disturbance to the archaeological record which may be preserved for future generations.



Obisidian Source	Projectile Point	Biface	Scraper	Other Formal Tool	Core	Flake	Untilized Flake	Worked Flake	Nodule	Angular Debris	Unspecified	TOTAL FROM SOURCE	% Sourced
Obsidian Cliff	157	26	0	2	2	623	93	42	0	16	4	965	68.29
Teton Pass	28	2	1	0	4	76	10	5	0	0	0	126	8.92
Bear Gulch	16	0	0	0	0	45	8	7	0	2	0	78	5.52
Absaroka (Twilight Pass)	1	1	0	1	1	37	6	0	0	2	7	56	3.96
Malad	15	3	0	0	0	27	2	2	0	3	0	52	3.68
Crescent H	7	2	0	0	0	30	5	3	0	0	0	47	3.33
Lava Creek Tuff	14	0	0	0	0	17	1	2	0	1	0	35	2.48
Wild Horse Canyon	1	1	0	0	0	8	1	0	0	0	0	11	0.78
Pack Saddle Creek	0	1	0	0	1	5	0	0	0	1	0	8	0.57
Conant Creek Tuff	1	0	0	0	0	2	1	1	0	0	0	5	0.35
Philips Pass	0	0	0	0	0	1	1	1	0	0	0	3	0.21
West Gros Ventre Butte	1	0	0	0	0	2	0	0	0	0	0	3	0.21
Brown's Bench	1	0	0	0	0	1	0	0	0	0	0	2	0.14
Big South Butte	0	0	0	0	0	2	0	0	0	0	0	2	0.14
Park Point	1	0	0	0	0	0	0	0	0	0	0	1	0.07
Source Uncertain	2	0	0	0	0	11	3	1	0	1	0	18	1.27
Timber Butte	1	0	0	0	0	0	0	0	0	0	0	1	0.07
Not Sourced	87	37	2	0	18	9138	289	92	229	191	220	10303	
TOTAL RECORDED	333	73	3	3	26	10025	420	156	229	217	231	11716	100.00

Figure 1: Map of identified obsidian sources in Western North America.
Table 1: Counts of EXRF sourced and un-sourced obsidian by the GRSLE project per artifact type.

Setup

Differential use of obsidian sources by precontact peoples has been used to infer mobility patterns and occupations in the Absaroka mountains, Wyoming. Identifying sources of obsidian involves measuring the relative abundances of trace elements using eXRF and analyzing clusters to differentiate sources. Using a large dataset of 1,842 obsidian artifacts, assembled by the GRSLE project, sourced using eXRF coupled with pXRF scans we assembled a logistic Bayesian model for predicting obsidian sources using just the results from pXRF. The model can identify samples from Obsidian Cliff in Yellowstone National Park with a better than 0.99 confidence. Using this modeling method and pXRF data greatly increases the feasibility in sourcing large assemblages of obsidian and provides a baseline for expanding our regional record.

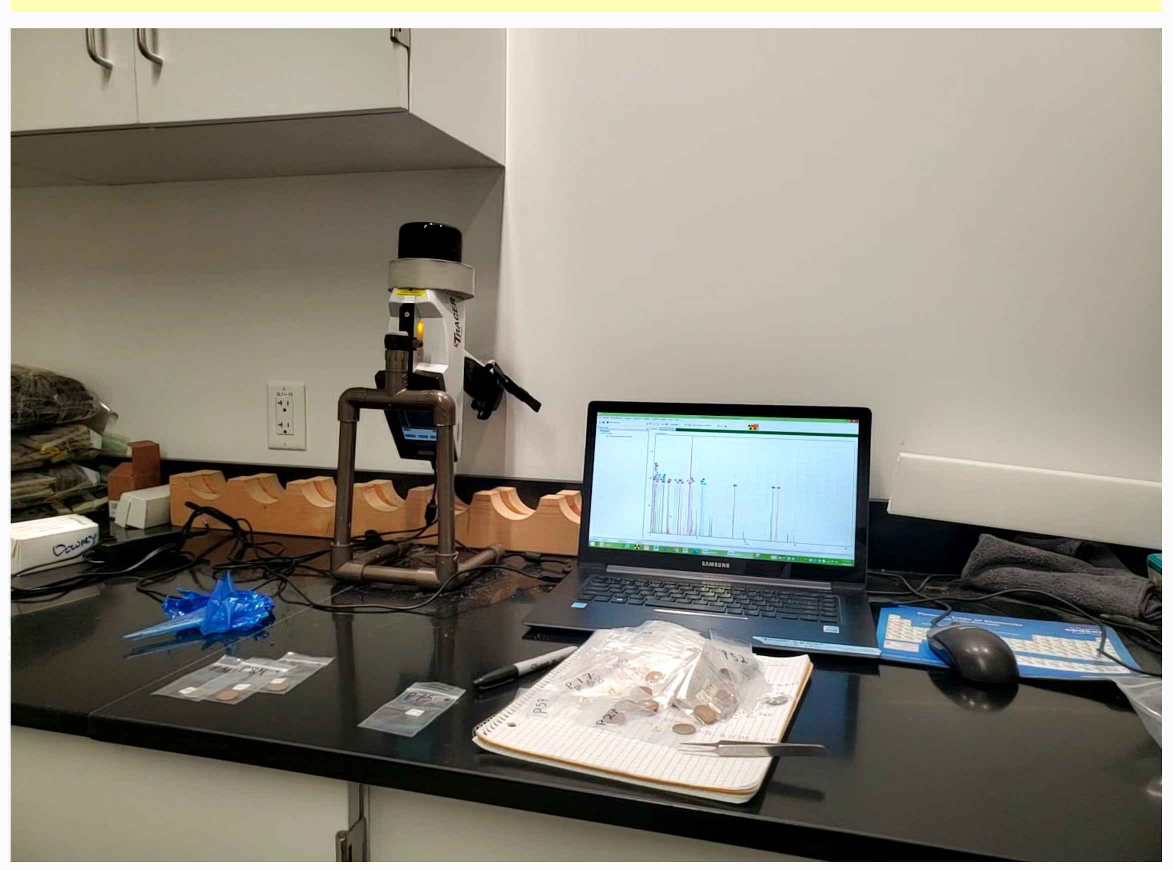


Figure 1: Bruker Tracer III-SD pXRF setup at the University of Utah's Red Lab in the Department of Geography.

pXRF Method

Obsidian artifacts were scanned using a Bruker Tracer III-SD pXRF. Artifacts were scanned for 30 seconds at a kV interval of [1, 40], uA = 11.6, with a Cu 100um: Ti 25um: Al 300 um filter wheel for 9 cycles. Comparisons between 30, 60 and 90 second scans produced no statistically significant difference in relative element abundances. Resulting data were processed using Artax to perform Bayesian Deconvolution.

Data

The complete GRSLE obsidian dataset includes 2,521 obsidian artifacts with elemental data. To assess the performance of machine learning techniques for identifying Obsidian Cliff a training dataset including 250 obsidian artifacts sourced by Richard Hughes and scanned with pXRF is used. The best performing model is then implemented to predict the posterior probability for Obsidian Cliff for 520 obsidian artifacts collected by GRSLE and scanned with pXRF.

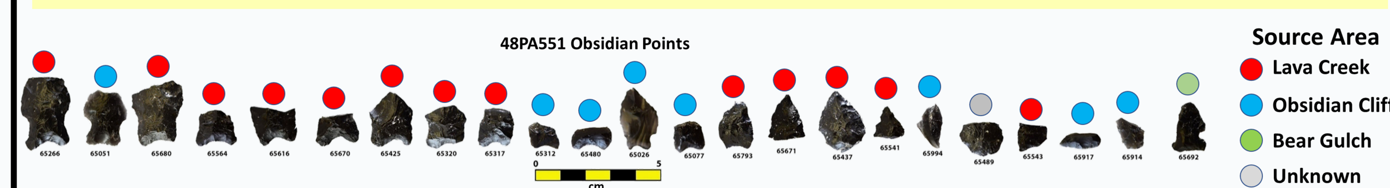


Figure 2: Sourced Obsidian projectile points.

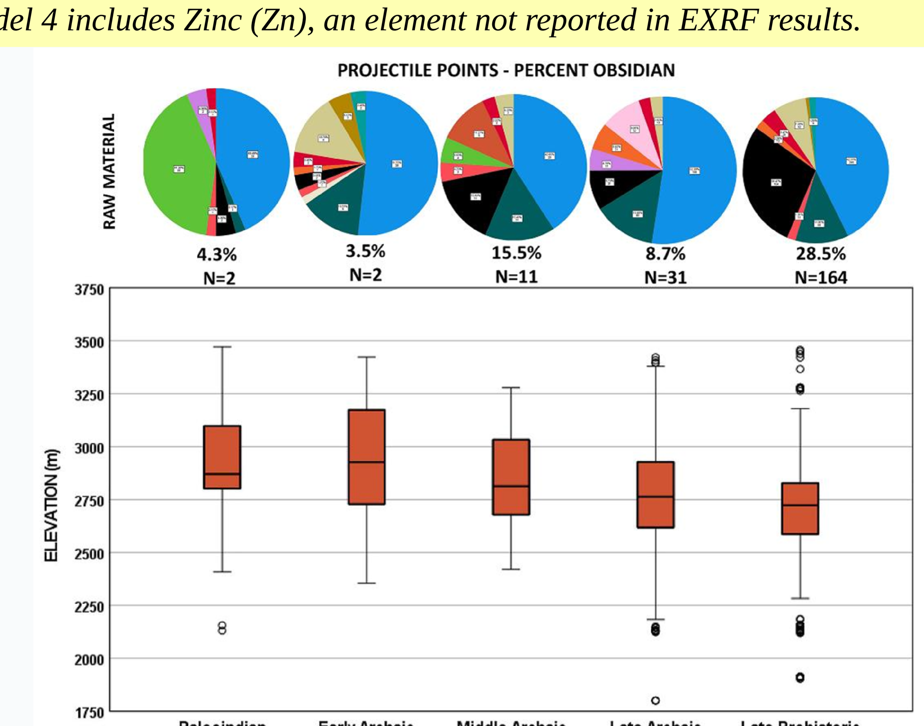
The Model

Permuting logistic regression models using all combinations of measured elements and comparing AICc values the final best fitting models included:

m1) *Obsidian Cliff ~ Nb, Rb, Sr, Y, and Zr*
m2) *Obsidian Cliff ~Nb, Rb, Sr, and Y*
m3) *Obsidian Cliff ~Rb, Sr, and Y*
m4)* *Obsidian Cliff ~Rb, Sr, Y, and Zn*

A training sample of 175 of the 250 EXRF and pXRF sourced artifacts is randomly selected while the remaining 75 specimens serve as the testing sample. Given the total number of possible combinations is $1.15e^{65}$ resampling was performed 10,000 times due to computational limitations.

Note: Model 4 includes Zinc (Zn), an element not reported in EXRF results.



AGE CLASS	N	%
Late Prehistoric	593	52.4
Late Archaic	362	32.0
Middle Archaic	71	6.3
Early Archaic	58	5.1
Paleoindian	47	4.2
TOTAL	1131	100.0

Figure 3: Proportion of obsidian projectile points by raw material and age class.

Model Selection

Bayesian model selection optimization was implemented to identify the best fitting modeling method given the training dataset. Bayesian optimization tests classification models and hyperparameters to identify the best performing fit. All draws and permutations of the training set identified Bayesian Neural Networks (BNN) as the best performing modeling technique using *log-loss* minimization. BNN's was the best performing technique across all 10,000 permutations.

Validation loss (*log-loss*) is calculated during model optimization to assess model selection performance. Often the estimated minimum validation loss converged with the observed minimum over relatively few iterations suggesting good performance.

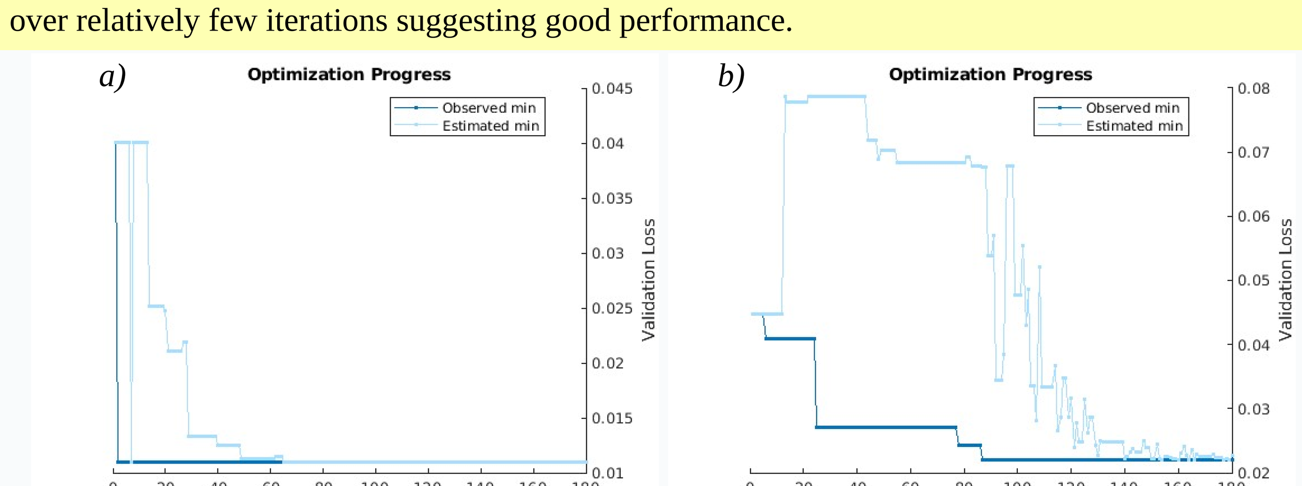


Figure 4: a) example of a quick convergence for model optimization compared to b) a prolonged convergence.

Model Comparison

All iterations (with the exception of m4) for each model were compared across the 10,000 random samples between the models built with EXRF and pXRF data. EXRF outperformed pXRF 90.1% of the time with the average number of miss-classifications for EXRF = 0.8 and for pXRF = 1.1. Notably, nearly 10% of pXRF models out-performed the EXRF models.

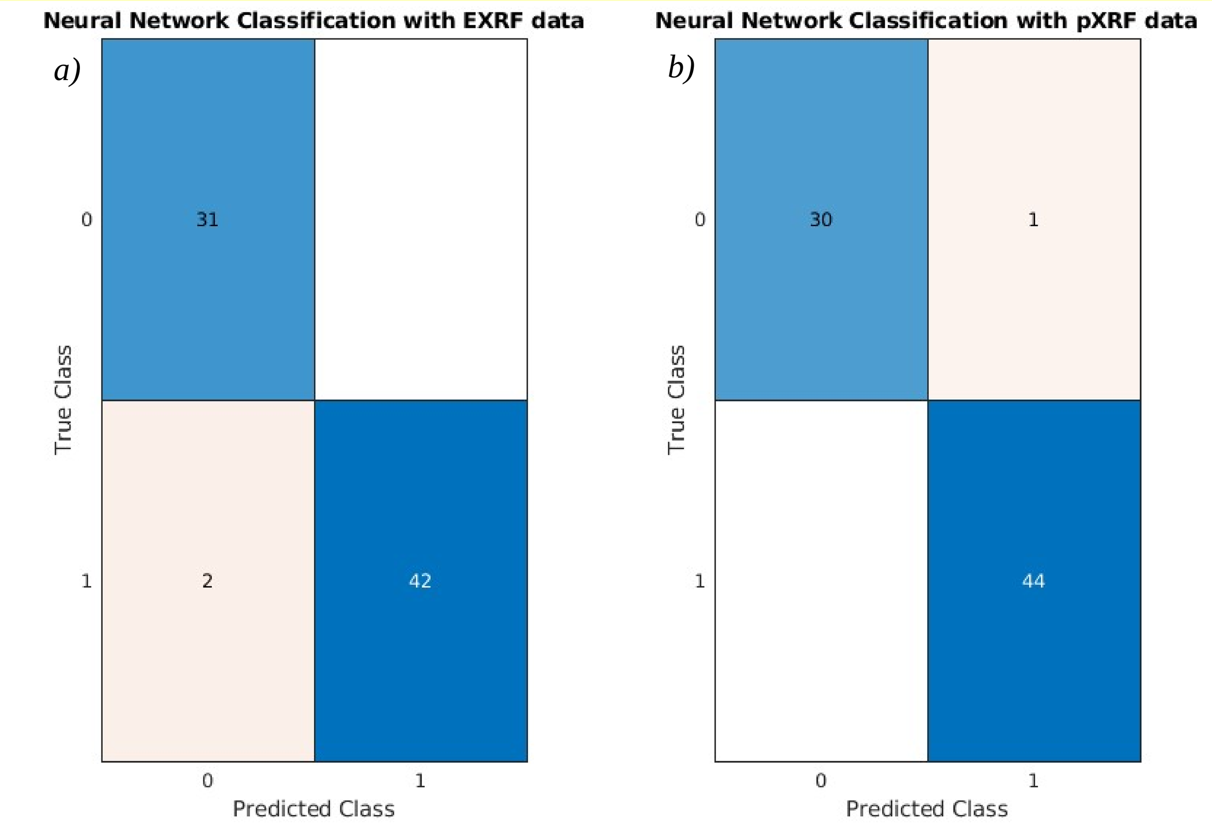


Figure 5: Example of BNN classification results using confusion plots where a) EXRF was out-performed by b) pXRF.

For each of the four sets of parameters final models were constructed using pXRF data for the entire 250 specimens with both EXRF and pXRF source data. The final models were then compared for the number of miss-identifications using the known source provided by EXRF reports. Overall, the best performance was by model 4 (m4) using Rubidium, Strontium, Yttrium and Zinc.

For identifying obsidian from Obsidian Cliff, Wyoming Niobium and Zirconium tended to produce poorer model fits when compared to the aforementioned best fitting parameters. It is worth noting that the set of non-Obsidian Cliff sources in this dataset include: Bear Gulch, Crescent Hill, Malad, Teton Pass, and Twilight Plateau. Broadening the potential variance in non-Obsidian Cliff relative element abundances could change the best performing set of parameters.

Source Selection

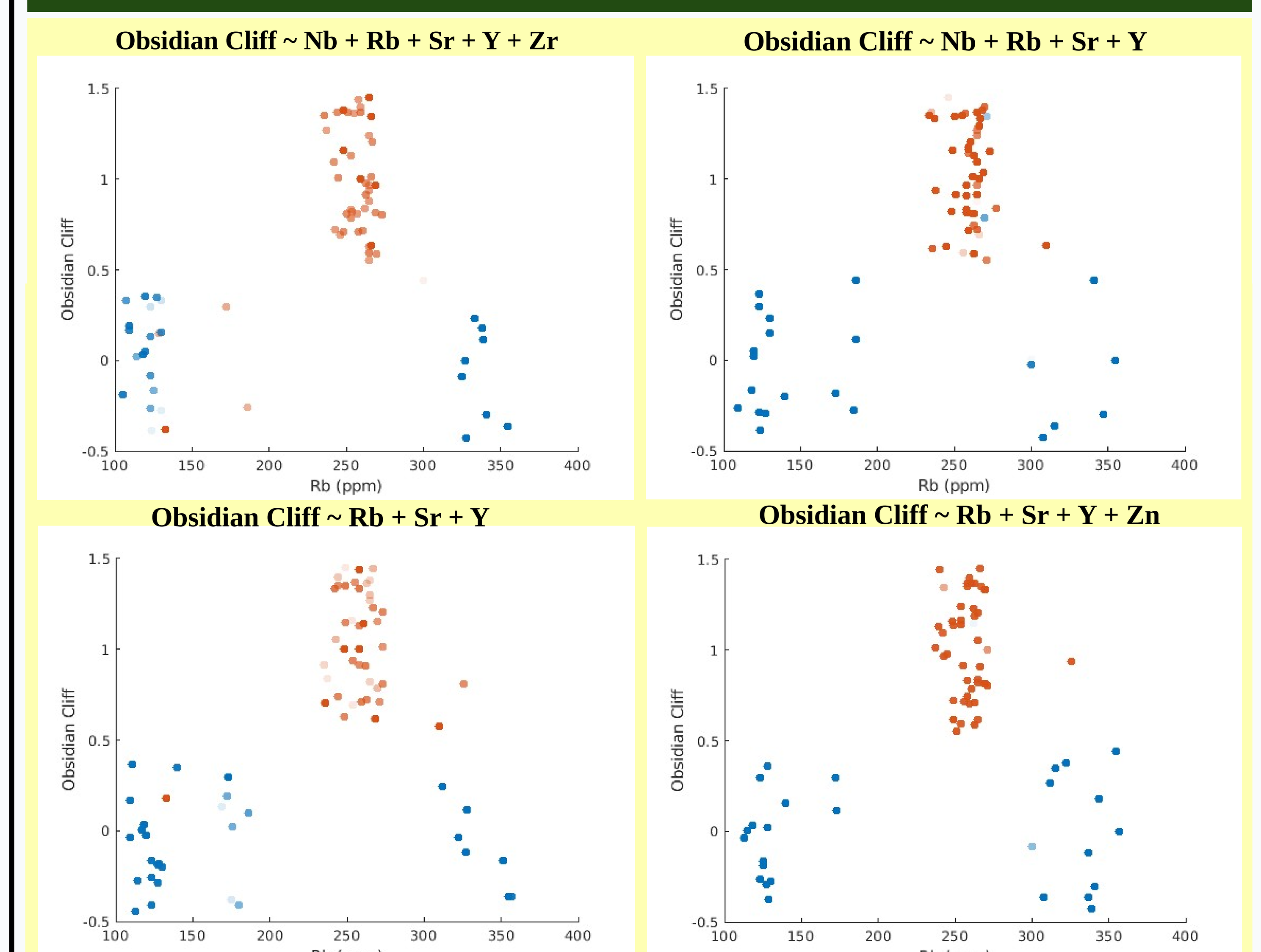


Figure 6: Comparison of model performances with the 250 sourced obsidian artifacts. Red indicates the posterior probability suggests Obsidian Cliff while blue indicates non-Obsidian Cliff. Color scales from darker = posterior probability ~1 to lighter = posterior probability near 0.5. The x-axis provides measures of Rubidium (the best performing single parameter for identifying Obsidian Cliff) in parts per million (ppm) and the y-axis is the unadjusted probabilities.

Broader Impacts

The potential for sourcing Obsidian artifacts in the field aids in reducing disturbance of archaeological materials by removing the need to displace artifacts for laboratory analysis. Field sourcing promotes the GRSLE Project's goal of minimizing disturbance through intensive field recording and "catch and release" archaeology.

Results & Implications

1) Bayesian Neural Networks were the best performing modeling technique for sourcing Obsidian Cliff obsidian.
2) The best fitting BNN model included Rubidium (Rb), Strontium (Sr), Yttrium (Y), and Zinc (Zn).

- *Though, all four models had predictive confidences >0.95

Using this model and just a 30 second pXRF scan we can identify Obsidian Cliff obsidian with >0.99 predictive confidence.

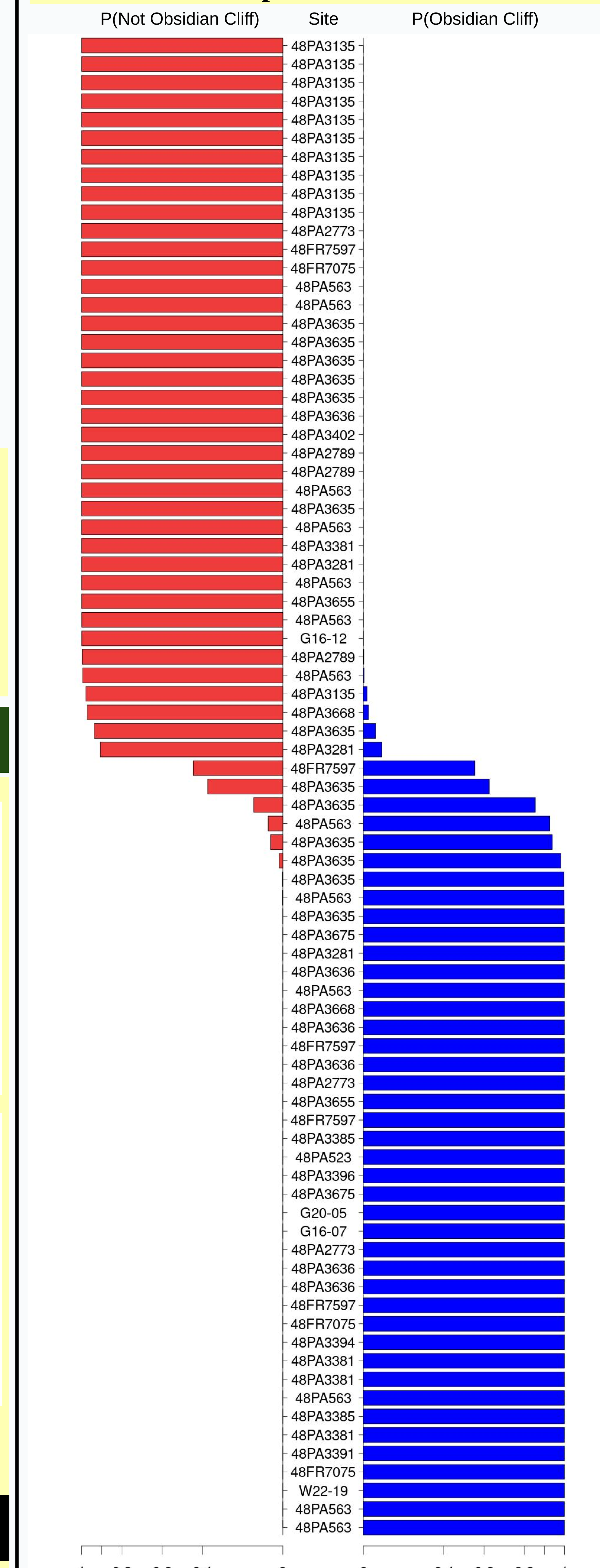


Figure 6: Predicted posterior probabilities for Obsidian Cliff obsidian, using model 4 (m4), centered on samples with probabilities <0.98. Probability of Obsidian Cliff was predicted for 520 samples with 398 identified as Obsidian Cliff.

Acknowledgments

Special thanks to the University of Utah's Red Lab in the Department of Geography for providing access to and training for their pXRF devices. We would also like to thank the Shoshone National Forest for their continued support of the GRSLE project.