Predictive Lithologic Mapping with Self-Organizing Maps of the Caçapava do Sul region, Southern Brazil

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INTRODUCTION

Airborne gamma-spectrometry and magnetometry were used to produce a predictive lithologic map of the Caçapava do Sul region in the State of Rio Grande do Sul through Self-Organizing Maps (SOM) (Kohonen, 2001). An important district with several occurrences of base and precious metals hosted on the Camaquã Basin Ediacaran rocks that lie over the Sul-riograndense Shield (Fig. 1).

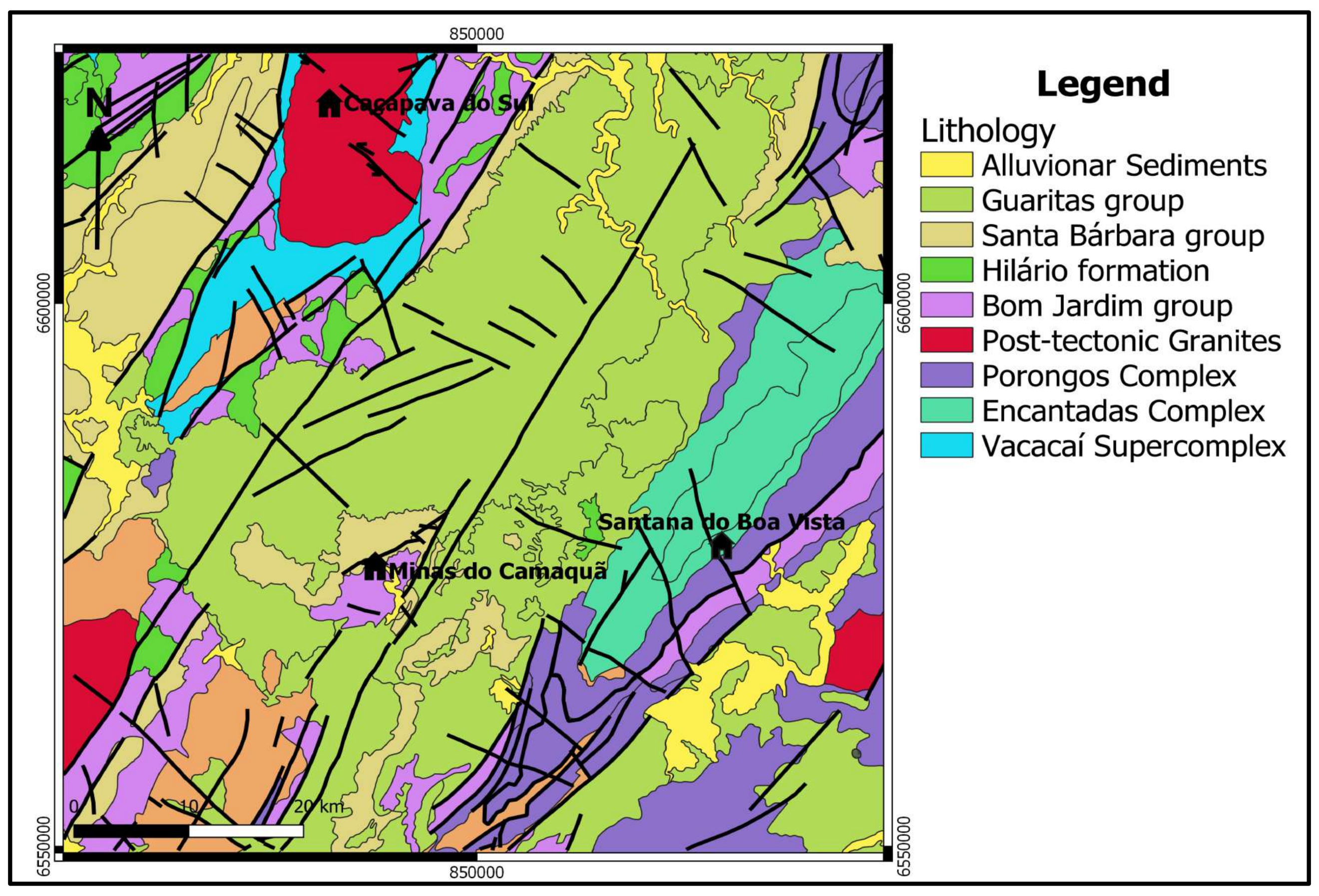

Figure 1: Geological map of the Camaquã Supergroup and the Basin basement units in the study area.

SOM allows us to build an unsupervised data-driven mapping (Carneiro *et al.*, 2012), which provides new insight into the lithologic knowledge of the area and may help define units poorly mapped due to the difficulties of the standard mapping techniques.

DATA AND PRE-PROCESSING

The airborne geophysical data provided by the Geological Survey of Brazil (GSB/CPRM) was used as input to train the SOM which includes potassium (K), equivalent thorium (eTh), equivalent uranium (eU), total count (TC), analytic signal (AS) and elevation (Fig. 2). The SOM derived clustering performance was investigated in three case studies. Trial 1, with all parameters with normalized values from 0 to 1; Trial 2, with log transformation used in AS to reduce the data skewness; and Trial 3, no data transformation was applied.

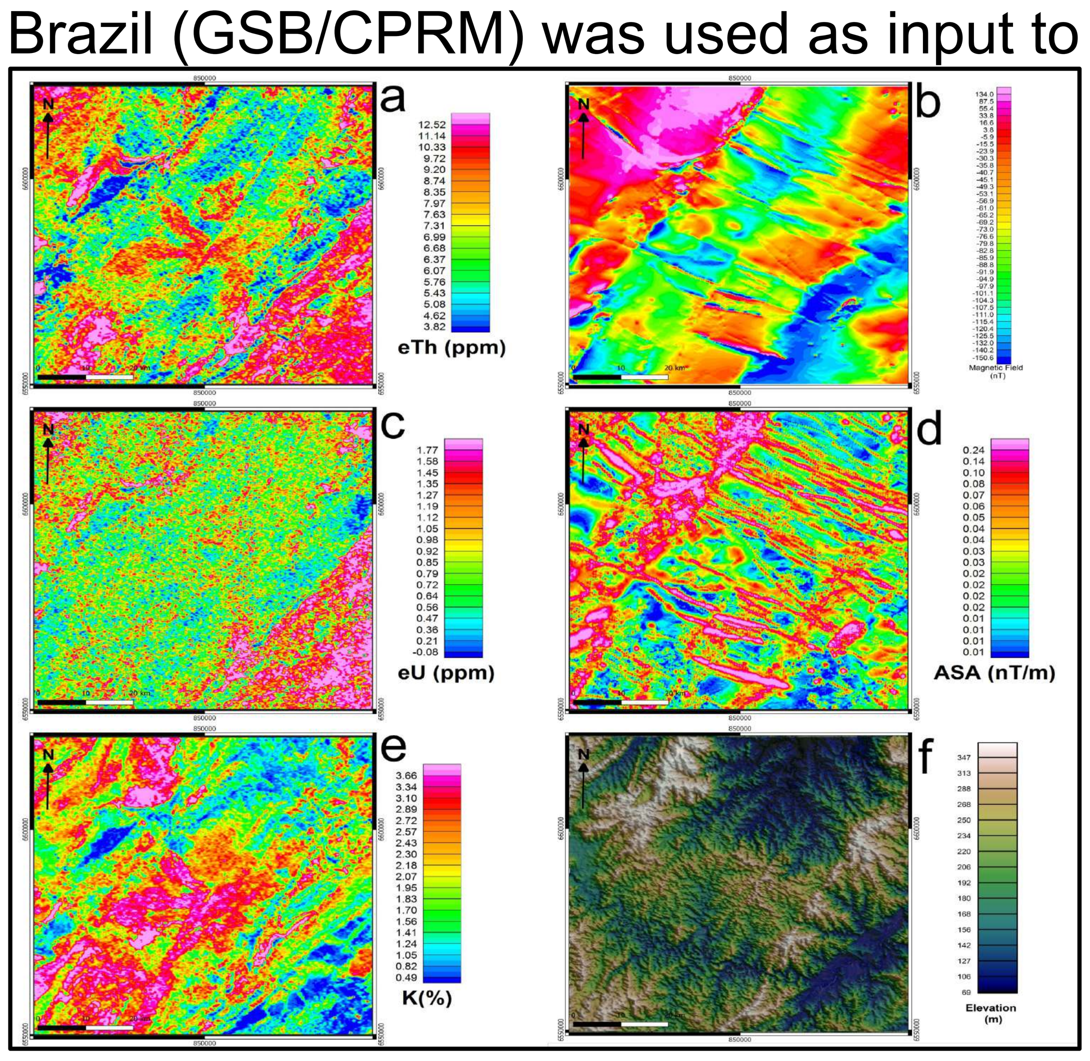

Figure 2: Maps of the airborne geophysical data used in this work a) eTh. b) Total Count (TC). c) eU. d) Analytical Signal (AS). e) K Signal. f) Elevation values.

METHODS

SOM is a type of Artificial Neural Network capable of reducing the data dimensionality, and representing it on a map, grouping similar data into the same cluster. For this work, the algorithm was best configured with a hexagonal lattice on a toroidal hypervolume map of 62 x 62.

After training, 17 was chosen as the optimum number of clusters based on the Davies-Bouldin index (Davies and Bouldin, 1979), which can be plotted and compared with the lithologic mapping of the area.

RESULTS

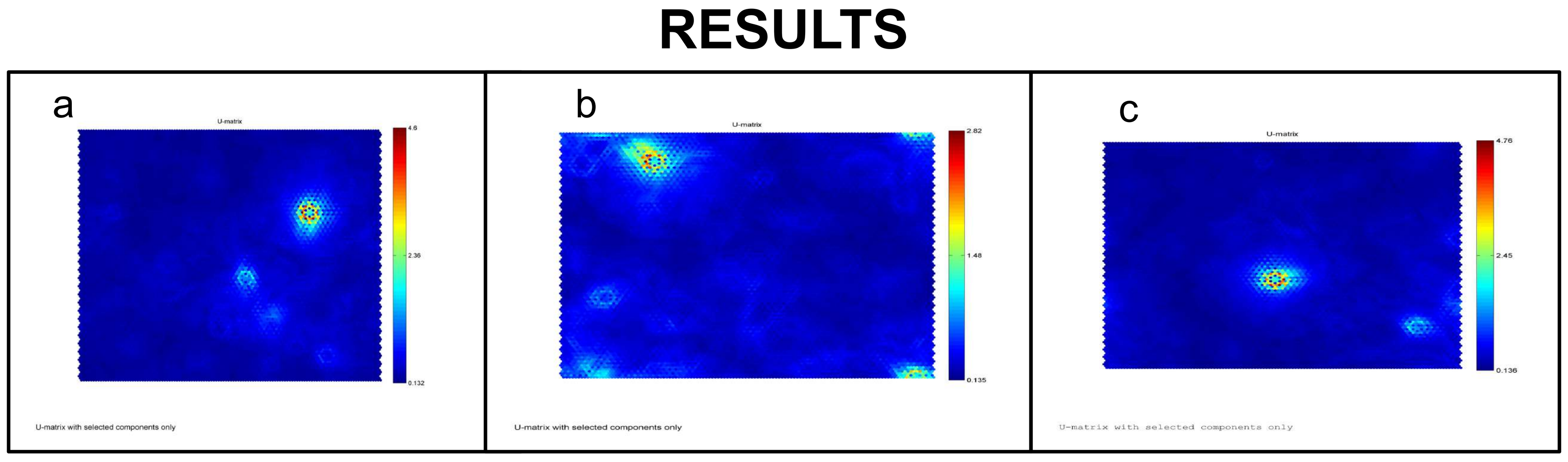

Figure 3: a) U-Matrix for Trial 1, b) U-Matrix for Trial 2, c) U-Matrix for Trial 3.

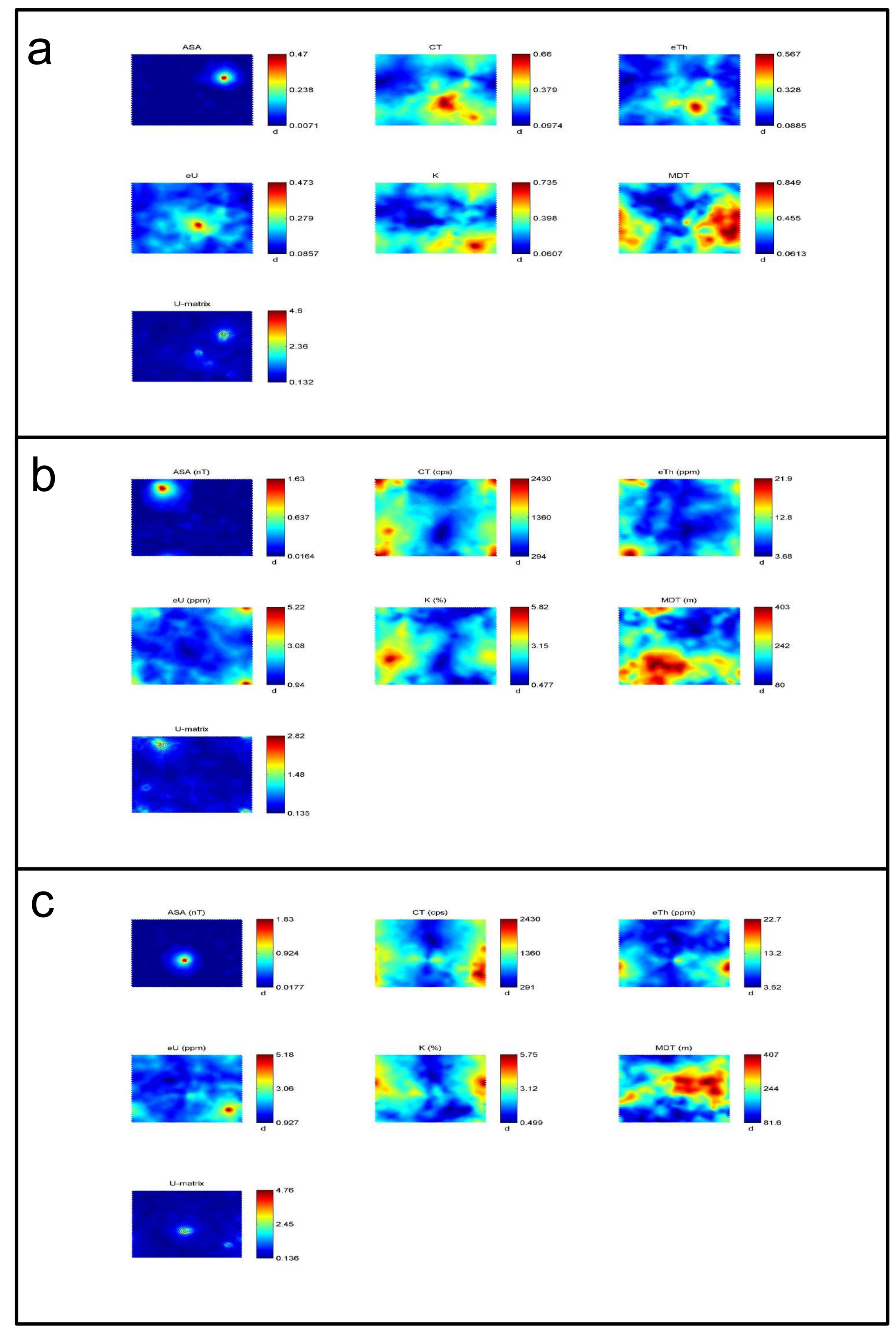

Figure 4: Component plots for: a) Trial 1; b) Trial 2; c) Trial 3.

The U-matrix (Fig. 3) are one way of representing the result of SOM analysis, where cooler colors indicate similarity between the nodes and warmer ones indicate dissimilarity. This organization allows us to cluster the data according to the number already decided by the Davies-Bouldin index (DBI).

According to the component plots (Fig. 4) is possible to see how the inputs influence the final map. In Trial 1, AS, eU and eTh were responsible for higher values in U-Matrix. In Trial 2, AS was the most influential, but the gamma-ray data values were also important. In Trial 3, AS and eU were responsible for the higher dissimilarities.

All three case studies show similar results (Fig. 5), where geological units match with equivalent DBI clusters, only with minor changes on their boundaries (contacts). Some clusters are remarkably similar to units in the last published geological map by Laux *et al.,* (2021), especially dykes, granites and volcanic rocks. On the other hand, the sedimentary rocks present a high uncertainty among the units. It may suggest new lithological sub-divisions, which were not mapped on fieldwork due to the lack of outcrops or poor access.

Such work shows that the geologic map of regions interesting for mining, like Caçapava do Sul, can be improved by using this technique because it reveals the diversity of lithology that cannot always be mapped on traditional approaches.

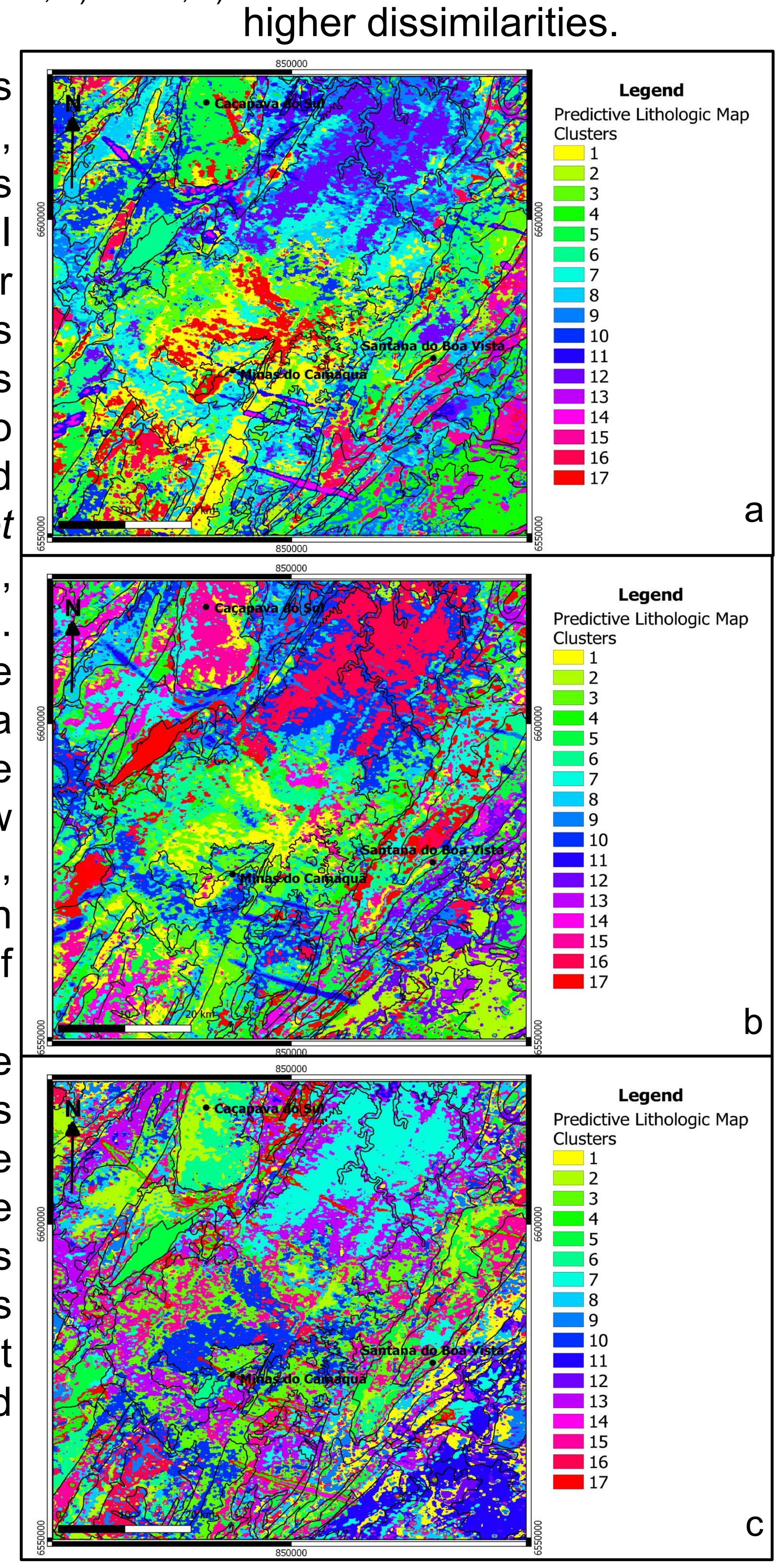

Figure 5: Predictive Lithologic Map for: a) Trial 1; b) Trial 2; c) Trial 3.

Carneiro, C. C., et al., 2012, Semiautomated geologic mapping using self-organizing maps and airborne geophysics in the Brazilian Amazon: Geophysics, 77, no. 4.
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Kohonen, T., 2001, Self-organizing maps: Springer.
Laux et al., 2021. Escudo Sul-Rio-Grandense, estado do Rio Grande do Sul. - CPRM, 2021.

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