Advances in Remote Sensing, 2025, 14(1), 44-59
https://www.scirp.org/journal/ars
ISSN Online: 2169-2688
ISSN Print: 2169-267X

Inversion of Chemical Elements in Laguocuo, Xizang Based on Sentinel-2 Satellite Data

Zhen Chen[1*], Qingkuan Li[2*], Shuli Wang[3], Xiaohong Sun[3]

[1]School of Earth Sciences and Resources, China University of Geosciences (Beijing), Beijing, China
[2]Qinghai Institute of Salt Lakes, Chinese Academy of Sciences, Xining, China
[3]Geology Institute of China Chemical Geology and Mine Bureau, Beijing, China
Email: *chenzhen@cugb.edu.cn

How to cite this paper: Chen, Z., Li, Q.K., Wang, S.L. and Sun, X.H. (2025) Inversion of Chemical Elements in Laguocuo, Xizang Based on Sentinel-2 Satellite Data. *Advances in Remote Sensing*, **14**, 44-59.
https://doi.org/10.4236/ars.2025.141004

Received: January 31, 2025
Accepted: March 9, 2025
Published: March 12, 2025

Abstract

Based on Sentinel-2 satellite data, this study conducted remote sensing inversion of chemical elements in Laguocuo Salt Lake, Xizang, in order to reveal the spatial distribution characteristics of lithium, potassium and other elements in the salt lake. Firstly, radiometric correction, atmospheric correction and geometric precision correction of the remote sensing images were carried out to ensure the high quality and reliability of the data. By combining the ground sampling data, the element inversion model is constructed by CART algorithm. The results show that the concentration of lithium in Laguocuo Salt Lake is high, especially in the central area of the lake, the concentration of lithium is significantly higher than other areas; while potassium, sodium and other elements in the salt lake showed a more uniform distribution. In addition, through the correlation analysis of the elements, it is found that there is a strong positive correlation between the concentrations of lithium and potassium and sodium, which indicates that these elements may have a common enrichment mechanism during the evaporation and concentration process of the salt lake. The research also shows that Laguocuo Salt Lake has a high development potential for lithium resources, and is one of the important areas for lithium resources exploration in salt lakes on the Qinghai-Xizang Plateau. Through remote sensing inversion technology, this study provides a scientific basis for resource assessment and sustainable management of Laguocuo Salt Lake, and provides a new technical idea for resource exploration of similar salt lakes.

Keywords

Sentinel-2 Satellite Data, Laguocuo Salt Lake, Chemical Element Inversion, Remote Sensing Technology, Lithium Resources, Spatial Distribution, CART Algorithm, Element Enrichment Mechanism

1. Introduction

The salt lake on the Qinghai-Xizang Plateau is one of the most important inland salt lake distribution areas in the world. It is rich in strategic mineral resources such as lithium and potassium. In recent years, with the rapid development of the new energy industry, especially the electric vehicle industry, the demand for lithium has increased significantly, and the lithium resources in the salt lake in Xizang have attracted more and more attention [1]. Traditional salt lake exploration methods rely on ground sampling and laboratory analysis, which are limited in time and cost [2]. Remote sensing technology, especially remote sensing inversion technology based on satellite data, provides a new idea for efficient and low-cost monitoring of salt lake resources [3].

The Sentinel-2 satellite, as part of the Copernicus program of the European Space Agency (ESA), has high-resolution, multi-spectral imaging capabilities and is very suitable for remote sensing retrieval of mineral and chemical elements in salt lakes [4]. Combined with ground measured data and remote sensing images, remote sensing inversion technology can establish a quantitative relationship between element concentration and remote sensing band by analyzing spectral characteristics, and then invert the spatial distribution of various elements in salt lakes [5]. CART (Classification and Regression Tree) algorithm, as a commonly used machine learning method, has been widely used in remote sensing inversion of elements in salt lake, and has achieved good inversion effect [6].

Although some remote sensing inversion of salt lake elements has been carried out in the Qinghai-Xizang Plateau, the research on Laguocuo Salt Lake is still limited. Based on Sentinel-2 satellite data, this study used CART algorithm to invert chemical elements (including lithium, potassium, etc.) in Laguocuo Salt Lake, aiming to reveal its element distribution characteristics and provide scientific basis for regional resource assessment and sustainable development.

2. Overview of Regional Geology

Salt lakes in Xizang are widely distributed in alpine basins and arid grassland areas in the interior of the Qinghai-Xizang Plateau. They were formed under the strong geological movement and arid climate conditions of the plateau. As the highest distribution area of salt lakes in the world, the formation of salt lakes in Xizang is closely related to regional tectonic activities and climate change [7]. Most of these salt lakes are located in plateau areas above 4000 meters above sea level and have complex geological structures, which are mainly controlled by crustal uplift on the Qinghai-Xizang Plateau [8]. Geological studies have shown that the salt lakes in Xizang are closely related to the tectonic activities of the plateau fault zones and basin margins. These salt lakes are not only natural recorders of geological environment and climate change, but also rich in various strategic mineral resources such as potassium, lithium and boron [9].

Located in the southeast of Xizang, Laguocuo Salt Lake is a typical inland salt lake. The geological background of the lake is influenced by the Himalayan

Mountains and the Qinghai-Xizang Plateau tectonic belt, forming a salt lake sedimentary environment with special geological characteristics [10]. The geological background of the region shows that the mineral composition of the salt lake is diverse, including sodium, potassium, magnesium and other minerals, and the distribution and enrichment of these minerals are closely related to the hydrological conditions and climate change of the salt lake [11]. In recent years, with the application of remote sensing technology, researchers have gradually revealed the spatial distribution laws of minerals and chemical elements in salt lakes in Xizang, providing important data support for the sustainable development of resources [12]. The remote sensing map of Laguocuo is shown in **Figure 1**.

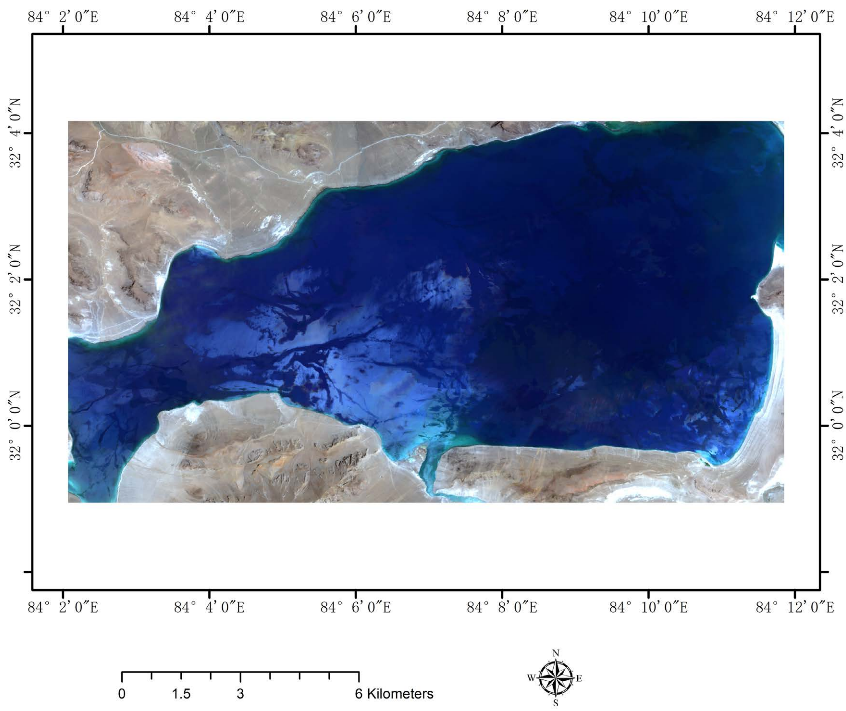

Figure 1. Remote sensing map of Laguocuo.

Laguocuo Salt Lake is located in the central part of the Qinghai-Xizang Plateau, within the Gangdese metallogenic belt, and has a complex geological background. Its basement consists of ancient metamorphic rocks rich in various metallic elements, while Cenozoic sedimentary rocks provide the material foundation for the surrounding areas through weathering and erosion. The region lies at the forefront of the collision between the Indian Plate and the Eurasian Plate, characterized by intense tectonic activity and well-developed fractures, which serve as pathways for element migration. Volcanic activity has introduced abundant chemical elements and triggered hydrothermal alteration, altering the chemical composition of the rocks. The hydrogeological conditions are complex, with lake water recharge primarily derived from atmospheric precipitation, snowmelt, and groundwater. The processes of runoff and discharge influence the distribution of elements, while the pH and redox potential of the lake water also affect the forms and stability of these elements. The lake's sediments are mainly composed of carbonate minerals, sulfate minerals, and clay minerals, which have the capacity to adsorb and enrich different elements. The redox conditions of the sedimentary environment further influence element distribution. These geological factors collectively contribute to the complex distribution and enrichment characteristics of geochemical elements in Laguocuo Salt Lake.

3. Methods

In this study, Sentinel-2 satellite data were used to conduct remote sensing inversion of chemical elements (including lithium, potassium, sodium, etc.) in Laguocuo Salt Lake, Xizang, mainly including remote sensing data preprocessing, inversion model construction and verification. Firstly, radiometric correction, atmospheric correction and geometric precision correction were carried out on the original remote sensing image to remove atmospheric interference and instrument errors and ensure the accuracy of the data [13]. Radiometric correction uses complementary correction methods based on Landsat 8 and Sentinel-2 [14].

Secondly, the spatial distribution of chemical elements is constructed using inversion models. After comparing CART (Classification and regression tree) and RF (Random forest) algorithms, we choose CART (Classification and regression tree) method in machine learning algorithm, which can effectively deal with multi-variable data and is especially suitable for modeling nonlinear relationships [15]. The input of CART model is the spectral feature of remote sensing image, and the output is the predicted value of element concentration. In order to improve the accuracy of the model, we also combined the ground measured data to train and verify the model.

Finally, the model was verified by cross-validation method. Different ground data sets were used to train and test the model, and the accuracy and reliability of the model were evaluated. Through the analysis of the inversion results, we can reveal the spatial distribution characteristics of various chemical elements in the salt lake and provide data support for the subsequent resource evaluation [16].

In the inversion study of chemical elements in Salt Lake, Sentinel-2 satellite image and ground chemical sample data were used to infer the distribution of chemical elements through machine learning algorithm. First, remote sensing data and representative salt lake samples were collected to obtain spectral information and chemical element concentration.

Next, spectral features, such as reflectivity and water index, are extracted from remote sensing images and matched with elemental concentrations of ground samples to form a training dataset. A machine learning algorithm, such as CART, was used to train the model to capture the nonlinear relationship between spectral features and element concentrations.

Finally, cross-validation is applied to evaluate the accuracy of the model and error analysis is performed. The trained model was applied to the salt lake image to predict the concentration of chemical elements, and to draw a spatial distribution map to reveal the distribution of elements in the target area.

3.1. Cart Algorithm

CART algorithm is a decision tree method based on recursive splitting, which constructs the inversion model of element concentration by partitioning spectral feature data [17]. The core of spectral feature matching is to maximize the purity of the data at each split node or minimize the regression error by selecting the optimal split point [18].

3.1.1. Splitting Criteria

In the regression task, CART algorithm uses Mean Squared Error (*MSE*) as the splitting criterion, which is used to measure the splitting effect of spectral features, and the formula is as follows [19]:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \bar{y}\right)^2$$

y_i is the true element concentration value of the i th sample; $\bar{y}$ is the mean value of sample concentration of the current node; N is the total number of samples of the current node.

CART algorithm minimizes the weighted *MSE* of the left and right sub-nodes after splitting by selecting a spectral band and corresponding splitting threshold:

$$Cost\left(s, j\right) = \frac{N_L}{N} MSE_L + \frac{N_R}{N} MSE_R$$

N_L and N_R are the numbers of samples of the left and right child nodes respectively; MSE_L and MSE_R are the mean squared errors of the left and right child nodes respectively.

3.1.2. Mapping of Spectrum to Element Concentration

By recursive splitting, spectral reflectance features are mapped to a relational model of the concentration of the target element.

$$\hat{y} = \frac{1}{N_{leaf}}\sum_{i=1}^{N_{leaf}} y_i$$

$\hat{y}$ is the predicted value of the leaf node; N_{leaf} is the total number of samples within the leaf nodes.

3.1.3. Spectrum Matching Is Realized

The specific process of CART algorithm in the inversion of spectral reflectance and salt lake element concentration includes: searching all spectral bands and splitting points to determine the optimal splitting rule; according to the optimal splitting point, the data is divided into left and right sub-nodes, and the corresponding relationship between spectral characteristics and element concentration is refined layer by layer. By constructing multi-layer tree structure, the nonlinear distribution of element concentration is approximated.

3.2. Random Forest Algorithm

In the multi-element inversion of lithium, potassium and other elements in the plateau salt lake, the random forest algorithm is used to match the spectral features, mainly by constructing the nonlinear mapping relationship between the reflectance spectrum and the element content, and mining the key bands or combination bands that are sensitive to the element content in the spectral characteristics, so as to achieve the inversion of the target elements.

3.2.1. Principle and Spectrum Matching of Random Forest Algorithm

Random Forest (RF) is an ensemble learning algorithm that can effectively process high-dimensional data and solve nonlinear regression problems by constructing multiple decision trees and synthesizing their prediction results. Spectral feature matching is based on the following core steps of random forest:

Spectral feature extraction and input variable construction, input variables include the spectral reflectance feature of the target salt lake region $X = \{x_1, x_2, \cdots, x_n\}$ and corresponding element concentration data $Y = \{y_1, y_2, \cdots, y_n\}$. Multi-spectral band reflectance values obtained from Sentinel-2 data are used as model inputs, where X_i represents the spectral reflectance of the I-th pixel over multiple bands, and Y_i represents the target element concentration of the pixel [20].

3.2.2. Feature Importance Evaluation and Key Band Selection

Random Forest assesses the importance of spectral features by calculating "decline in mean square error" or "decline in Gini index". Its formula is:

$$\Delta MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \widehat{y_i}\right)^2 - \left(y_i - \widehat{y_i}\right)^2$$

where, $\widehat{y_i}$ is the predicted value of the original model. $\widehat{y_i'}$ is the predicted value after excluding a certain spectral band. According to the feature importance score, the band combination that is most sensitive to the inversion of the target element can be screened out.

3.2.3. Construction of Regression Model

The core of random forest is to generate multiple training samples by introducing Bootstrap Sampling, and train a regression decision tree independently on each sample. The prediction rule for each tree is based on the splitting principle of minimizing Mean Squared Error (*MSE*):

$$MSE = (1/N)\sum_{i=1}^{N}\left(y_i - \dot{y}_i\right)^2$$

At the time of each node splitting, some spectral features are randomly selected for optimal splitting, thus reducing the collinearity problem of high-dimensional data.

3.2.4. Spectral Mapping with Element Concentration

The final inversion model realizes the nonlinear mapping between spectral characteristics and element concentration by synthesizing the prediction results of all decision trees. The specific prediction value is calculated as follows:

$$\dot{Y} = (1/T)\sum_{t=1}^{T} f_t(X)$$

where, T is the total number of decision trees in the forest, $f_t(X)$ representing the prediction results of the T-th tree.

3.3. Remote Sensing Inversion Model Selection

In multi-element inversion, it is very important to select a suitable inversion model. In this study, through the comparison of different models, CART (classification and regression tree) algorithm was used to invert 15 elements such as K^+, Na^+, Ca^{2+}, Mg^{2+}, Cl^-, SO_4^{2-}, HCO_3^{2-}, CO_3 Li, BO_2, Br, Rb, Sr, I and Cs in the salt lake. The inversion model was evaluated by cross-validation method, and the inversion results were compared and analyzed by combining the measured data in the laboratory. The verification results show that there is a high correlation between the inversion results and the measured values, especially for lithium and potassium, which have high inversion accuracy and can better reflect the actual element distribution in the salt lake.

The accuracy of CART algorithm is higher than that of random forest (RF) when Sentinel-2 remote sensing images are used to invert chemical elements in salt lake. This phenomenon may be due to a number of factors: with a smaller dataset, CART ADAPTS better because it performs superior on small datasets, while RF generally requires a larger data volume to reduce overfitting; in addition, CART makes more efficient use of high correlation features, while RF may lose diversity due to high correlation of features, resulting in reduced performance.

In addition, the model complexity of CART is lower, the adjustment is more intuitive, and the overfitting problem is easy to control. In contrast, RF may not perform as well as CART when computing resources are limited or undertuned due to the excessive number of parameters and the need for more computational resources and hyperparameter tuning. RF is also more sensitive to data noise, which CART can reduce through simple pruning and other techniques.

CART models are also more explanatory, helping researchers understand the relationship between chemical elements and spectral features. Although RF is superior in many cases, CART may be more accurate in specific salt lake chemical element retrieval tasks due to factors such as data characteristics, feature selection, and scene adaptability. Therefore, it is recommended to further compare the models and optimize the parameters to select the most suitable algorithm.

This study utilized Sentinel-2 remote sensing data to invert the geochemical elements of Laguo Cuo Salt Lake in Xizang. The results indicate that the inversion accuracy of the CART algorithm is significantly higher than that of the Random Forest (RF) algorithm, which can be attributed to the following reasons: Firstly, with a limited sample size, the CART algorithm is better able to capture the nonlinear relationships between element concentrations and remote sensing bands, whereas the RF algorithm is prone to overfitting or underfitting when data is insufficient. Secondly, the high correlation among bands in the remote sensing images of the salt lake allows CART to automatically select the most influential features for the target variable through recursive partitioning, thereby constructing a concise and efficient model. In contrast, RF's random feature selection may overlook critical information. Additionally, the relatively simple structure of the CART model, combined with its intuitive parameter tuning and strong interpretability, enables effective noise control through techniques such as pruning, further enhancing the model's stability. In summary, the limitations in data volume, high inter-feature correlation, and differences in model complexity and noise-handling capabilities collectively determine that the CART algorithm outperforms the Random Forest algorithm under the conditions of this study.

3.4. Precision Analysis

In Salt Lake chemical element inversion research, evaluating the accuracy of the machine learning model is a key step to ensure the reliability of the inversion results. Commonly used accuracy evaluation indicators include the coefficient of determination (R^2), which represents the proportion of the total variation of the target variable explained by the model, and the higher the value, the better the model fits. The advantage of R^2 is that it is intuitive and easy to understand, making it useful for comparison between models, but it has the disadvantage of being sensitive to outliers, potentially overestimating model performance, and failing to reflect predicted biases. Therefore, while R^2 may reflect the explanatory power of the model, increasing R^2 does not necessarily mean that the prediction is more accurate and may lead to overfitting, especially in complex models.

In this project, the CART (Classification and Regression Tree) algorithm is used to perform multi-element inversion in the salt lake. CART algorithm is a nonlinear data mining method, which can deal with high-dimensional and complex relational data, and is suitable for inversion modeling between multi-spectral images and multi-element concentrations. CART generates a decision tree structure by recursively dividing the data set into multiple subsets to minimize the error or impurity after splitting. The algorithm has strong flexibility and robustness, and can handle a variety of different data features, which is especially suitable for multi-element inversion research.

In practical operation, firstly, the spectral features related to the concentration of each element are extracted by using the information of different bands in remote sensing images, such as spectral reflectance and spectral index. Then, the CART algorithm is used to train these feature variables and build the inversion model of each element. In the model training, the element concentration measured in the laboratory is taken as a reference, and the parameters are iteratively adjusted to improve the prediction accuracy of the model for multi-element concentration. Finally, the reconstructed model is used to invert the remote sensing image and generate the spatial distribution map of various elements in Laguocuo fault. The accuracy analysis of the model is shown in the following **Figures 2-3**.

After comparing Cart and Random Forest algorithm, the inversion accuracy of Cart algorithm is 0.92, while the inversion accuracy of Random Forest algorithm is 0.88. Therefore, this study adopts Cart algorithm to invert the chemical elements of Lago Salt Lake.

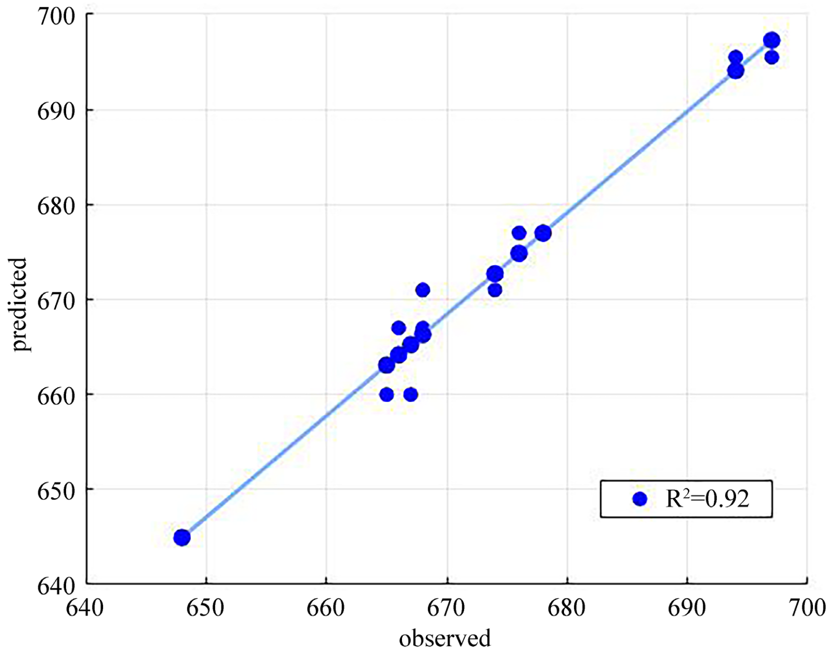

Figure 2. Accuracy of the Laguocuo lake inversion by Cart algorithm $R^2 = 0.92$.

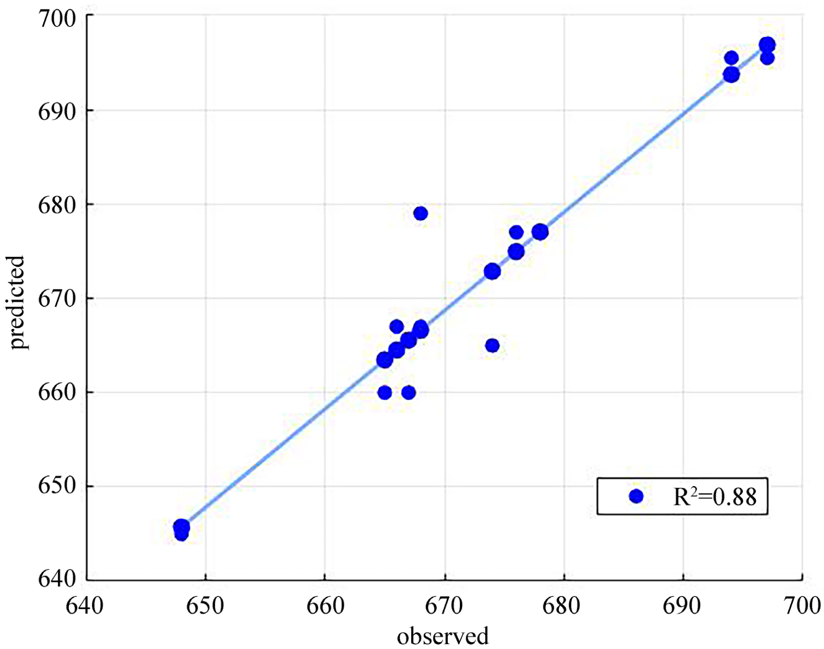

Figure 3. The accuracy of Random forest algorithm's Laguocuo lake inversion $R^2 = 0.88$.

4. Results

Based on Sentinel-2 satellite data, remote sensing inversion of chemical elements (such as lithium, potassium, sodium, magnesium, etc.) in Laguocuo Salt Lake, Xizang was carried out in this study, and the spatial distribution map of each element was obtained. A sampling grid with a fixed spacing of 2000 meters was pre-established throughout the entire salt lake area, with a total of 31 sampling points laid out to ensure even and representative coverage. After collection, the brine samples were bottled, sealed, and labeled, and then transported to the laboratory under low-temperature conditions, ensuring the scientific and standardized nature of the sampling process. The inversion results show that there are obvious spatial differences in the distribution of lithium elements in the lake, especially in the southeast of the lake, the concentration of lithium is high, while in the peripheral area, the concentration of lithium is gradually reduced. The distribution characteristics are closely related to the hydrological conditions and evaporation and concentration process of the salt lake, indicating that the lithium enrichment in this area has great development potential.

The distribution of potassium and sodium elements is relatively uniform, but the concentration of potassium is slightly higher in the northwestern part of the lake, which may be related to the strong evaporation and enrichment of water bodies in this area. In contrast, the distribution of magnesium is more dispersed, mainly concentrated in the southwest part of the lake, forming a more significant high concentration area. This suggests that the hydrological and geological background of the region may have played an important role in the enrichment of magnesium.

By analyzing the spatial characteristics of element distribution, it is found that the concentration of elements in the central area of the salt lake is generally higher, while the concentration of elements in the outer area is gradually decreasing. In addition, there is a strong positive correlation between lithium, potassium and sodium, indicating that the enrichment mechanism of these elements in the salt lake may be similar. Inversion map of Laguocuo Li element based on Gaofen-5 and cart algorithm is shown in Figure 4.

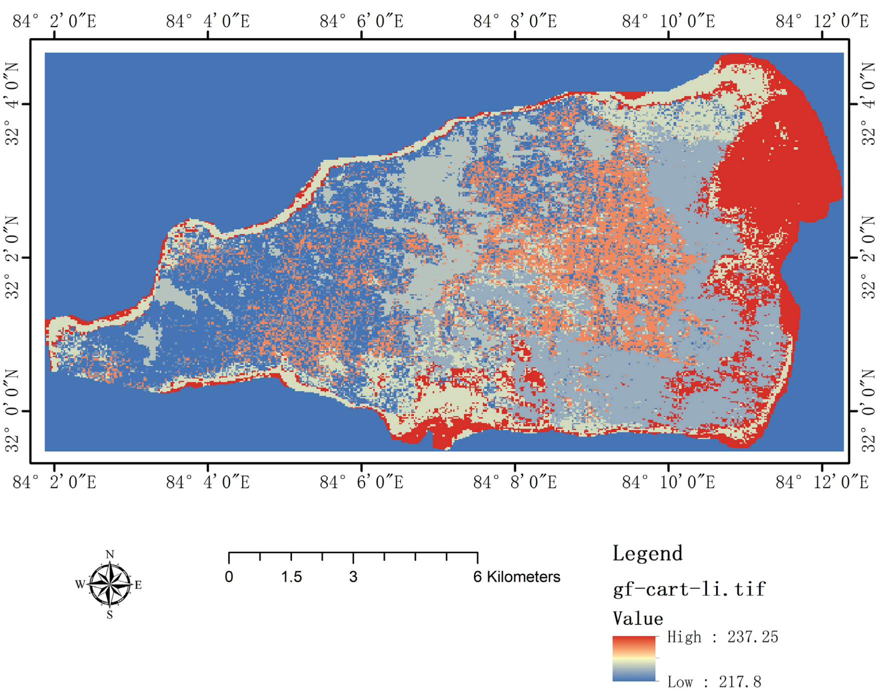

Figure 4. Inversion map of Laguocuo Li element based on Gaofen-5 and cart algorithm.

Element inversion map of Laguocuo Li based on Gaofen-5 and RF Random forest algorithm is shown in **Figure 5**.

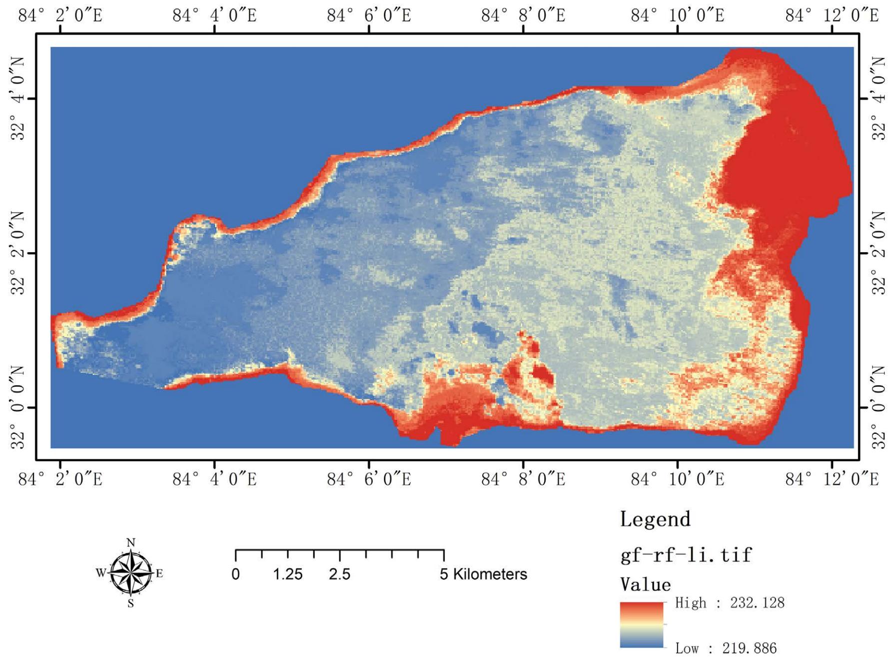

Figure 5. Element inversion map of Laguocuo Li based on Gaofen-5 and RF Random forest algorithm.

Element inversion map of Laguocuo Li based on sentinel2 and CART algorithm is shown in **Figure 6**.

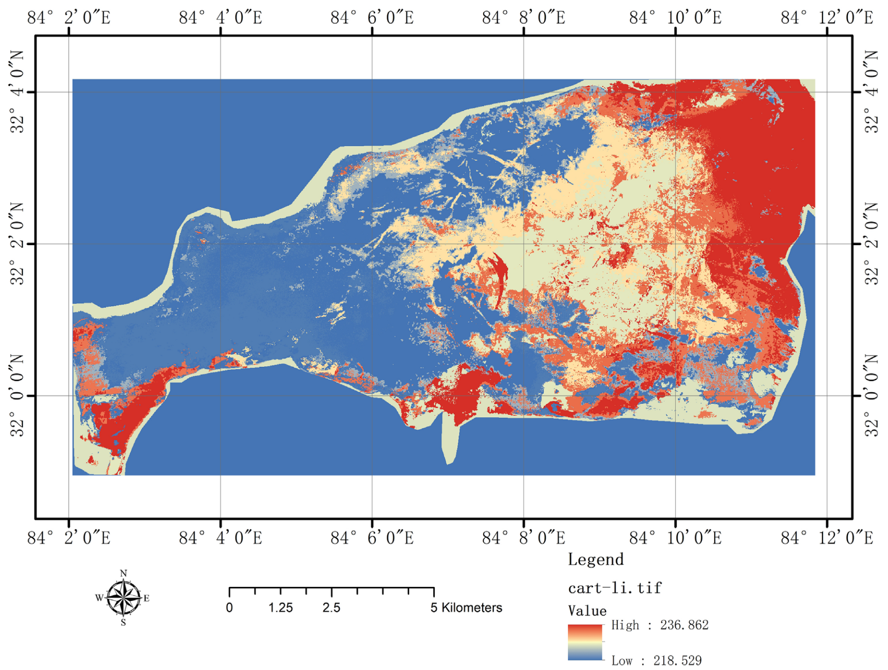

Figure 6. Element inversion map of Laguocuo Li based on sentinel2 and CART algorithm.

Element inversion map of Laguocuo Li based on sentinel2 and RF random forest algorithm is shown in Figure 7.

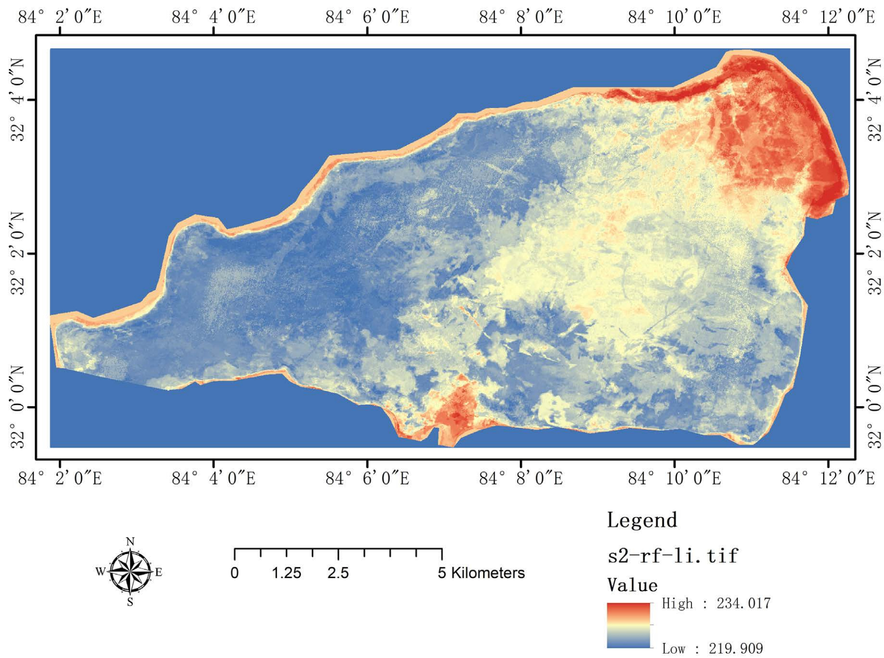

Figure 7. Element inversion map of Laguocuo Li based on sentinel2 and RF random forest algorithm.

5. Discussion

Through the analysis of remote sensing inversion results of chemical elements in Laguocuo Salt Lake, the following important conclusions can be drawn. Firstly, the distribution of lithium in the salt lake shows obvious spatial heterogeneity. The concentration of lithium in the central area is higher, while that in the peripheral area is lower, which is closely related to the hydrological conditions of the salt lake and the effect of evaporation and concentration. As Laguocuo Salt Lake is a typical arid salt lake, evaporation is the main mechanism of lithium enrichment, so this area has a high potential for lithium resource development.

Secondly, the distribution of potassium and sodium is relatively uniform, and potassium is slightly enriched in the northwest region, indicating that the evaporation effect in this region has played a role in promoting the enrichment of potassium. The distribution of sodium is relatively stable, which may be due to the high solubility of sodium in salt lake water and the small impact of climate change. The distribution of magnesium is more complex, concentrated in the southwest of the lake, which may be related to the geological background and hydrological flow characteristics of the area.

Through the correlation analysis of different elements, it is found that there is a strong positive correlation between lithium, potassium and sodium elements, indicating that the enrichment mechanism of these elements in the salt lake is similar, which may be controlled by common hydrological and geological processes. In addition, the correlation between the elements provides a valuable basis for further understanding of the resource development of the salt lake, indicating that the Laguocuo Salt Lake has relatively rich mineral resources, especially the development potential of strategic resources such as lithium and potassium.

In the Laguocuo Salt Lake, the correlation analysis of element concentration shows that the correlation between lithium, sodium and potassium is high, and calcium and magnesium also show a strong correlation, which may be related to their common enrichment characteristics in the evaporation and concentration process of the salt lake. For example, potassium, sodium and chloride ions are mainly derived from rock weathering and evaporation, while magnesium ions and sulfate ions are related to the crystallization of magnesium sulfate salts. Lithium also shows specific correlations with borate, strontium, rubidium, and cesium plasmas, reflecting enrichment patterns of elements in salt lakes.

The enrichment mechanisms of these elements are influenced by evaporation and concentration, mineral precipitation and chemical reactions. With the evaporation of water, the concentration of dissolved ions in brine increases, potassium, sodium, chlorine and other elements show synchronous changes, while lithium and borate are enriched in the late evaporation. During mineral precipitation, the differentiation of carbonate minerals and sulfate minerals leads to the separation of calcium from carbonate and bicarbonate ions. The elements such as lithium, rubidium and cesium in the late brine are enriched by ion competition and form specific minerals in the high salinity environment. These studies provide an important scientific basis for understanding the metallogenic regularity of salt lakes and strategic resource development.

The remote sensing inversion method for geochemical elements in salt lakes is highly efficient, advanced, and scalable. By utilizing satellite remote sensing data and integrating machine learning algorithms (such as the CART algorithm), this method can rapidly and efficiently obtain the spatial distribution of elements like lithium, potassium, sodium, and magnesium in salt lakes. Compared with traditional methods, remote sensing inversion overcomes the drawbacks of discontinuous data and time-consuming processes, significantly improving monitoring efficiency. Moreover, this method has demonstrated good applicability in the assessment of salt lake resources in different regions, providing important technical support for the rapid evaluation and development of salt lake resources.

6. Conclusions

Based on Sentinel-2 satellite data, this study conducted inverse analysis of chemical elements in Laguocuocuo Salt Lake, Xizang, and drew the following conclusions. Firstly, the distribution of various chemical elements in the salt lake showed obvious spatial differences, especially lithium, potassium and magnesium. The enrichment area of lithium is mainly concentrated in the center of the lake, while the distribution of potassium and sodium elements is more uniform. Magnesium is mainly concentrated in the southwest of the lake, indicating that the distribution of elements in the salt lake is influenced by hydrological conditions, evaporation effect and geological background. Secondly, there is a significant correlation between the elements, lithium, potassium, sodium and other elements showed a strong positive correlation, suggesting that the enrichment mechanism of these elements in the salt lake is similar.

The findings of this study are of great significance for resource assessment and development of the salt Lake of Laguocuo. Firstly, remote sensing inversion provides an effective tool to accurately evaluate the spatial distribution of chemical elements in the salt lake, and provides a scientific basis for resource exploration and development. Secondly, the research results provide a valuable reference for understanding the hydrogeological mechanism of element enrichment in salt lakes. Through further field investigation and experimental analysis, the potential of salt lake resources and the best plan for their exploitation and utilization can be better revealed.

Future studies can further deepen the exploration of the relationship between the hydrological environment and element distribution of the salt lake, and combine other remote sensing data and ground observation data to improve the accuracy of the inversion model, so as to provide more reliable data support for the sustainable development of the salt lake resources.

7. Acknowledgements

This work was supported by the National Science and Technology Major Project, Earth Deep Exploration and Mineral Resources Exploration (Grant No. 2024ZD1002004), and the Science and Technology Innovation Project of China National Administration of Coal Geology (Grant No. ZMKJ-2023-JBGS03-02). The authors gratefully acknowledge the financial support provided by these projects, which made this research possible.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Ding, T., Zheng, M., Nie, Z., Ma, L., Ye, C., Wu, Q., *et al.* (2022) Impact of Regional Climate Change on the Development of Lithium Resources in Zabuye Salt Lake, Xizang. *Frontiers in Earth Science*, **10**, Article 865158. https://doi.org/10.3389/feart.2022.865158

[2] Lin, Y.J., Zheng, M.P. and Liu, X.F. (2017) Boron Resource of Salt Lakes in Qinghai-Xizang Plateau. *Science & Technology Review*, **35**, 77-82

[3] Zhi, H., Mao, F., Ding, L.L., Yuan, Y.R., Li, D.K., He, M.D., Liu, L. and Wang, C.A. (2022) Salinity Inversion of a Low Salinity Lake Based on Sentinel-2 Multispectral Remote Sensing: A Case Study of the Co Ngoin Lake in Xizang. *Journal of Fishery Sciences of China*, **29**, 355-364.

[4] Kong, F., Yang, Y., Luo, X., Sha, Z., Wang, J., Ma, Y., *et al.* (2021) Deep Hydrothermal and Shallow Groundwater Borne Lithium and Boron Loadings to a Mega Brine Lake

in Qinghai Xizang Plateau Based on Multi-Tracer Models. *Journal of Hydrology*, **598**, Article ID: 126313. https://doi.org/10.1016/j.jhydrol.2021.126313

[5] Liu, T., Dai, J., Zhao, Y., Tian, S. and Ye, C. (2021) Remote Sensing Inversion of Lithium Concentration in Salt Lake Using Light GBM: A Case Study of Northern Zabuye Salt Lake in Xizang. *Acta Geologica Sinica*, **95**, 2249-2256.

[6] Ma, R., Yang, G., Duan, H., Jiang, J., Wang, S., Feng, X., *et al.* (2010) China's Lakes at Present: Number, Area and Spatial Distribution. *Science China Earth Sciences*, **54**, 283-289. https://doi.org/10.1007/s11430-010-4052-6

[7] Sun, A., Yang, Q., Liu, Z., Chen, H., Han, L., Jiang, S., *et al.* (2021) Distribution of Wetlands and Salt Lakes in the Yadong Region of Xizang Based on Remote Sensing, and Their Geo-Climatic Environmental Changes. *China Geology*, **5**, 1-12. https://doi.org/10.31035/cg2022039

[8] Sun, A., Yang, Q., Liu, Z., Chen, H., Han, L., Jiang, S., *et al.* (2021) Distribution of Wetlands and Salt Lakes in the Yadong Region of Xizang Based on Remote Sensing, and Their Geo-Climatic Environmental Changes. *China Geology*, **5**, 1-12. https://doi.org/10.31035/cg2022039

[9] Li, Z.Y., Li, B.K., He, M., Wen, X.Q. and Di Zhou, J. (2024) The Source of Lithium in Lakkor Co Salt Lake on Qinghai-Xizang Plateau, China: Evidence from Hydrochemical Characteristics and Boron Isotope. *Acta Geochimica*, **43**, 933-946. https://doi.org/10.1007/s11631-024-00697-z

[10] Li, B., He, M., Ma, H., Cheng, H. and Ji, L. (2022) Boron Isotope Geochemistry of Bangor Co Salt Lake (central Xizang): Implications for Boron Origin and Uneven Mixing of Lake Water. *Acta Geochimica*, **41**, 731-740. https://doi.org/10.1007/s11631-022-00542-1

[11] Wang, J., Liu, J., Li, Z., Liu, D. and Wang, D. (2015) High Resolution Remote Sensing Estimation of Salinity in Salt Lake with Uranium Resources. *Journal of Earth Science*, **40**, 1409-1414.

[12] Abdelhamid, G. and Rabba, I. (1994) An Investigation of Mineralized Zones Revealed during Geological Mapping, Jabal Hamra Faddan—Wadi Araba, Jordan, Using Landsattm Data. *International Journal of Remote Sensing*, **15**, 1495-1506. https://doi.org/10.1080/01431169408954179

[13] Wang, J., Lu, D., Zhou, M., Wu, D. and Hao, W. (2021) WV-II High Resolution Data Based Quantitative Inversion of Salinity Content for Salt Lake: A Case Study of Gasikule Salt Lake. *Uranium Geology*, **37**, 78-86.

[14] Xu, W., Bu, L., Kong, W., Zheng, M. and Nie, Z. (2017) Monitoring of the Dynamic Change of Zabuye Salt Lake: A Remote Sensing Approach. *Science & Technology Review*, **35**, 89-96.

[15] Sam, S.C. and Balasubramanian, G. (2023) Spatiotemporal Detection of Land Use/Land Cover Changes and Land Surface Temperature Using Landsat and MODIS Data across the Coastal Kanyakumari District, India. *Geodesy and Geodynamics*, **14**, 172-181. https://doi.org/10.1016/j.geog.2022.09.002

[16] Zhang, D., Tian, S. and Luan, X. (2007) Remote Sensing Research on the Spatial Distribution of Boric Anhydride in the Zhabuye Salt Lake of Xizang. *Remote Sensing for Land & Resources*, **19**, 32-35.

[17] Slavković, M., Stamenković, M., Milanović, M. and Sretenović, S. (2024) Direction for Remote Sensing Supportive Role in Remote Working: Cart Algorithm Application for Monitoring and Self-Discipline Determination. *International Journal for Quality Research*, **18**, 567-586.

[18] Liang, Y., Huang, D., Chen, Y., Meng, Y. and Zhu, J. (2024) Optimization on

Handling Stability Using Adaboost-Cart with an Improved Evolution Algorithm under Uncertainty. *Journal of Mechanical Science and Technology*, **38**, 6415-6429. https://doi.org/10.1007/s12206-024-1101-1

[19] Li, C., Cai, R., Tian, W., Yuan, J. and Mi, X. (2023) Land Cover Classification by Gaofen Satellite Images Based on CART Algorithm in Yuli County, Xinjiang, China. *Sustainability*, **15**, Article 2535. https://doi.org/10.3390/su15032535

[20] Arfa, A. and Minaei, M. (2024) Utilizing Multitemporal Indices and Spectral Bands of Sentinel-2 to Enhance Land Use and Land Cover Classification with Random Forest and Support Vector Machine. *Advances in Space Research*, **74**, 5580-5590. https://doi.org/10.1016/j.asr.2024.08.062