

References

1. Carranza, E.J.M.; Laborte, A.G. Data-driven predictive mapping of gold prospectivity, Baguio district, Philippines: Application of random forests algorithm. *Ore. Geol. Rev.* **2015**, *71*, 777–787. [[Google Scholar](#)] [[CrossRef](#)]
2. Yousefi, M.; Carranza, E.J.M. Geometric average of spatial evidence data layers: A GIS-based multi-criteria decision-making approach to mineral prospectivity mapping. *Comput. Geosci.* **2015**, *83*, 72–79. [[Google Scholar](#)] [[CrossRef](#)]
3. Porwal, A.; Carranza, E.J.M. Introduction to the special issue: GIS-based mineral potential modelling and geological data analyses for mineral exploration. *Ore. Geol. Rev.* **2015**, *71*, 477–483. [[Google Scholar](#)] [[CrossRef](#)]
4. Yousefi, M.; Nykänen, V. Introduction to the special issue: GIS-based mineral potential targeting. *J. Afr. Earth. Sci.* **2017**, *128*, 1–4. [[Google Scholar](#)] [[CrossRef](#)]
5. Rodriguez-Galiano, V.; Sanchez-Castillo, M.; Chica-Olmo, M.; Chica-Rivas, M. Machine learning predictive models for mineral prospectivity: An evaluation of neural networks, random forest, regression trees and support vector machines. *Ore. Geol. Rev.* **2015**, *71*, 804–818. [[Google Scholar](#)] [[CrossRef](#)]
6. Carranza, E.J.M. Geocomputation of mineral exploration targets. *Comput. Geosci.* **2011**, *37*, 1907–1916. [[Google Scholar](#)] [[CrossRef](#)]
7. Cheng, Q.; Agterberg, F.P. Fuzzy weights of evidence method and its application in mineral potential mapping. *Nat. Resour. Res.* **1999**, *8*, 27–35. [[Google Scholar](#)] [[CrossRef](#)]
8. Zuo, R.; Cheng, Q.; Agterberg, F.P. Application of a hybrid method combining multilevel fuzzy comprehensive evaluation with asymmetric fuzzy relation analysis to mapping prospectivity. *Ore. Geol. Rev.* **2009**, *35*, 101–108. [[Google Scholar](#)] [[CrossRef](#)]
9. Yousefi, M.; Nykänen, V. Data-driven logistic-based weighting of geochemical and geological evidence layers in mineral prospectivity mapping. *J. Geochem. Explor.* **2016**, *164*, 94–106. [[Google Scholar](#)] [[CrossRef](#)]
10. Li, B.; Liu, B.; Guo, K.; Li, C.; Wang, B. Application of a maximum entropy model for mineral prospectivity maps. *Minerals* **2019**, *9*, 556. [[Google Scholar](#)] [[CrossRef](#)]
11. Li, X.; Yuan, F.; Zhang, M.; Jia, C.; Jowitt, S.M.; Ord, A.; Zheng, T.; Hu, X.; Li, Y. Three-dimensional mineral prospectivity modeling for targeting of concealed mineralization within the Zhonggu iron orefield, Ningwu basin, China. *Ore. Geol. Rev.* **2015**, *71*, 633–654. [[Google Scholar](#)] [[CrossRef](#)]
12. Leite, E.P.; de Souza Filho, C.R. Probabilistic neural networks applied to mineral potential mapping for platinum group elements in the Serra Leste region, Carajás Mineral Province, Brazil. *Comput. Geosci.* **2009**, *35*, 675–687. [[Google Scholar](#)] [[CrossRef](#)]
13. Porwal, A.; Carranza, E.J.M.; Hale, M. Bayesian network classifiers for mineral potential mapping. *Comput. Geosci.* **2006**, *32*, 1–16. [[Google Scholar](#)] [[CrossRef](#)]
14. Singer, D.A.; Kouda, R. Classification of mineral deposits into types using mineralogy with a probabilistic neural network. *Nonrenew. Resour.* **1997**, *6*, 27–32. [[Google Scholar](#)] [[CrossRef](#)]
15. Carranza, E.J.M.; Hale, M. Logistic regression for geologically constrained mapping of gold potential, Baguio district, Philippines. *Explor. Min. Geol.* **2001**, *10*, 165–175. [[Google Scholar](#)] [[CrossRef](#)]

16. Li, X.; Yuan, F.; Zhang, M.; Jowitt, S.M.; Ord, A.; Zhou, T.; Dai, W. 3D computational simulation-based mineral prospectivity modeling for exploration for concealed Fe–Cu skarn-type mineralization within the Yueshan orefield, Anqing district, Anhui province, China. *Ore. Geol. Rev.* **2019**, 105, 1–17. [[Google Scholar](#)] [[CrossRef](#)]
17. Qin, Y.; Liu, L. Quantitative 3D association of geological factors and geophysical fields with mineralization and its significance for ore prediction: An example from Anqing orefield, China. *Minerals* **2018**, 8, 300. [[Google Scholar](#)] [[CrossRef](#)]
18. Zuo, R. Machine learning of mineralization-related geochemical anomalies: A review of potential methods. *Nat. Resour. Res.* **2017**, 26, 457–464. [[Google Scholar](#)] [[CrossRef](#)]
19. Lary, D.J.; Alavi, A.H.; Gandomi, A.H.; Walker, A.L. Machine learning in geosciences and remote sensing. *Geosci. Front.* **2016**, 7, 3–10. [[Google Scholar](#)] [[CrossRef](#)]
20. Wegner, J.; Roscher, R.; Volpi, M.; Veronesi, F. Foreword to the special issue on machine learning for geospatial data analysis. *Isprs. Int. J. Geo-Inf.* **2018**, 7, 147. [[Google Scholar](#)]
21. Lee, J.; Jang, H.; Yang, J.; Yu, K. Machine learning classification of buildings for map generalization. *Isprs. Int. J. Geo-Inf.* **2017**, 6, 309. [[Google Scholar](#)] [[CrossRef](#)]
22. Saljoughi, B.S.; Hezarkhani, A. A comparative analysis of artificial neural network (ANN), wavelet neural network (WNN), and support vector machine (SVM) data-driven models to mineral potential mapping for copper mineralizations in the Shahr-e-Babak region, Kerman, Iran. *Appl. Geomat.* **2018**, 10, 229–256. [[Google Scholar](#)] [[CrossRef](#)]
23. Chen, Y.; Wu, W.; Zhao, Q. A bat-optimized one-class support vector machine for mineral prospectivity mapping. *Minerals* **2019**, 9, 317. [[Google Scholar](#)] [[CrossRef](#)]
24. Sun, T.; Chen, F.; Zhong, L.; Liu, W.; Wang, Y. Gis-based mineral prospectivity mapping using machine learning methods: A case study from Tongling ore district, eastern China. *Ore. Geol. Rev.* **2019**, 109, 26–49. [[Google Scholar](#)] [[CrossRef](#)]
25. Li, T.; Xia, Q.; Zhao, M.; Gui, Z.; Leng, S. Prospectivity mapping for tungsten polymetallic mineral resources, Nanling metallogenic belt, south China: Use of random forest algorithm from a perspective of data imbalance. *Nat. Resour. Res.* **2019**. [[Google Scholar](#)] [[CrossRef](#)]
26. Zhang, N.; Zhou, K.; Li, D. Back-propagation neural network and support vector machines for gold mineral prospectivity mapping in the Hatu region, Xinjiang, China. *Earth. Sci. Inform.* **2018**, 11, 553–566. [[Google Scholar](#)] [[CrossRef](#)]
27. Zhang, Z.; Zuo, R.; Xiong, Y. A comparative study of fuzzy weights of evidence and random forests for mapping mineral prospectivity for skarn-type Fe deposits in the southwestern Fujian metallogenic belt, China. *Sci. China. Earth. Sci.* **2015**, 59, 556–572. [[Google Scholar](#)] [[CrossRef](#)]
28. Carranza, E.J.M.; Laborte, A.G. Random forest predictive modeling of mineral prospectivity with small number of prospects and data with missing values in Abra (Philippines). *Comput. Geosci.* **2015**, 74, 60–70. [[Google Scholar](#)] [[CrossRef](#)]
29. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, 521, 436–444. [[Google Scholar](#)] [[CrossRef](#)]
30. Young, T.; Hazarika, D.; Poria, S.; Cambria, E. Recent trends in deep learning based natural language processing. *IEEE Comput. Intell. M.* **2018**, 13, 55–75. [[Google Scholar](#)] [[CrossRef](#)]

31. Dekhtiar, J.; Durupt, A.; Bricogne, M.; Eynard, B.; Rowson, H.; Kiritsis, D. Deep learning for big data applications in CAD and PLM—Research review, opportunities and case study. *Comput. Ind.* **2018**, *100*, 227–243. [[Google Scholar](#)] [[CrossRef](#)]
32. Wang, Y.; Fang, Z.; Hong, H. Comparison of convolutional neural networks for landslide susceptibility mapping in Yanshan County, China. *Sci. Total. Environ.* **2019**, *666*, 975–993. [[Google Scholar](#)] [[CrossRef](#)] [[PubMed](#)]
33. Xiao, L.; Zhang, Y.; Peng, G. Landslide susceptibility assessment using integrated deep learning algorithm along the China-Nepal highway. *Sensors* **2018**, *18*, 4436. [[Google Scholar](#)] [[CrossRef](#)] [[PubMed](#)]
34. Zuo, R.; Xiong, Y.; Wang, J.; Carranza, E.J.M. Deep learning and its application in geochemical mapping. *Earth-Sci. Rev.* **2019**, *192*, 1–14. [[Google Scholar](#)] [[CrossRef](#)]
35. Miller, J.; Nair, U.; Ramachandran, R.; Maskey, M. Detection of transverse cirrus bands in satellite imagery using deep learning. *Comput. Geosci.* **2018**, *118*, 79–85. [[Google Scholar](#)] [[CrossRef](#)]
36. Xiong, Y.; Zuo, R.; Carranza, E.J.M. Mapping mineral prospectivity through big data analytics and a deep learning algorithm. *Ore. Geol. Rev.* **2018**, *102*, 811–817. [[Google Scholar](#)] [[CrossRef](#)]
37. Carranza, E.J.M.; van Ruitenbeek, F.J.A.; Hecker, C.; van der Meijde, M.; van der Meer, F.D. Knowledge-guided data-driven evidential belief modeling of mineral prospectivity in Cabo de Gata, SE Spain. *Int. J. Appl. Earth. Obs.* **2008**, *10*, 374–387. [[Google Scholar](#)] [[CrossRef](#)]
38. Feng, C.; Zhang, D.; Zeng, Z.; Wang, S. Chronology of the tungsten deposits in southern Jiangxi Province, and episodes and zonation of the regional W-Sn mineralization—evidence from high-precision zircon U-Pb, molybdenite Re-Os and muscovite Ar-Ar ages. *Acta. Geol. Sin-Engl.* **2012**, *86*, 555–567. [[Google Scholar](#)]
39. Feng, C.; Zeng, Z.; Zhang, D.; Qu, W.; Du, A.; Li, D.; She, H. Shrimp zircon U-Pb and molybdenite Re-Os isotopic dating of the tungsten deposits in the Tianmenshan-Hongtaoling W-Sn orefield, southern Jiangxi Province, China, and geological implications. *Ore. Geol. Rev.* **2011**, *43*, 8–25. [[Google Scholar](#)] [[CrossRef](#)]
40. Jingwen, M.; Yanbo, C.; Maohong, C.; Pirajno, F. Major types and time-space distribution of Mesozoic ore deposits in south China and their geodynamic settings. *Miner. Depos.* **2013**, *48*, 267–294. [[Google Scholar](#)] [[CrossRef](#)]
41. Mao, J.; Xie, G.; Guo, C.; Chen, Y. Large-scale tungsten-tin mineralization in the Nanling Region, south China: Metallogenic ages and corresponding geodynamic processes. *Acta Petrol. Sin.* **2007**, *23*, 2329–2338. [[Google Scholar](#)]
42. Zhao, W.W.; Zhou, M.F.; Li, Y.H.M.; Zhao, Z.; Gao, J.F. Genetic types, mineralization styles, and geodynamic settings of Mesozoic tungsten deposits in south China. *J. Asian. Earth. Sci.* **2017**, *137*, 109–140. [[Google Scholar](#)] [[CrossRef](#)]
43. Liang, X.; Dong, C.; Jiang, Y.; Wu, S.; Zhou, Y.; Zhu, H.; Fu, J.; Wang, C.; Shan, Y. Zircon U-Pb, molybdenite Re-Os and muscovite Ar-Ar isotopic dating of the Xitian W-Sn polymetallic deposit, eastern Hunan Province, south China and its geological significance. *Ore. Geol. Rev.* **2016**, *78*, 85–100. [[Google Scholar](#)] [[CrossRef](#)]
44. Yang, J.H.; Kang, L.F.; Peng, J.T.; Zhong, H.; Gao, J.F.; Liu, L. In-situ elemental and isotopic compositions of apatite and zircon from the Shuikoushan and Xihuashan granitic plutons: Implication for Jurassic granitoid-related Cu-Pb-Zn and W mineralization in the Nanling Range, south China. *Ore. Geol. Rev.* **2018**, *93*, 382–403. [[Google Scholar](#)] [[CrossRef](#)]

45. Yang, J.H.; Kang, L.F.; Liu, L.; Peng, J.T.; Qi, Y.Q. Tracing the origin of ore-forming fluids in the Piaotang tungsten deposit, south China: Constraints from in-situ analyses of wolframite and individual fluid inclusion. *Ore. Geol. Rev.* **2019**, *111*, 102939. [[Google Scholar](#)] [[CrossRef](#)]
46. Yang, J.H.; Zhang, Z.; Peng, J.T.; Liu, L.; Leng, C.B. Metal source and wolframite precipitation process at the Xihuashan tungsten deposit, south China: Insights from mineralogy, fluid inclusion and stable isotope. *Ore. Geol. Rev.* **2019**, *111*, 102965. [[Google Scholar](#)] [[CrossRef](#)]
47. Nanling Range Group of Ministry of Geology and Mineral Resources. Study on Regional Tectonic Characteristics and Ore-Forming Structures in the Nanling Range; Geology Publishing House: Beijing, China, 1988; p. 266. (In Chinese) [[Google Scholar](#)]
48. Fang, G.; Chen, Z.; Chen, Y.; Li, J.; Zhao, B.; Zhou, X.; Zeng, Z.; Zhang, Y. Geophysical investigations of the geology and structure of the Pangushan-Tieshanlong tungsten ore field, South Jiangxi, China—Evidence for site-selection of the 2000-m nanling scientific drilling project (SP-NLSD-2). *J. Asian. Earth. Sci.* **2015**, *110*, 10–18. [[Google Scholar](#)] [[CrossRef](#)]
49. GeoCloud Database of China Geological Survey. Available online: <http://geocloud.cgs.gov.cn> (accessed on 31 December 2019).
50. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [[Google Scholar](#)] [[CrossRef](#)]
51. Rodriguez-Galiano, V.F.; Chica-Olmo, M.; Chica-Rivas, M. Predictive modelling of gold potential with the integration of multisource information based on random forest: A case study on the Rodalquilar area, Southern Spain. *Int. J. Geogr. Inf. Sci.* **2014**, *28*, 1336–1354. [[Google Scholar](#)] [[CrossRef](#)]
52. Breiman, L.; Friedman, J.; Stone, C.J.; Olshen, R.A. Classification and Regression Trees; Chapman and Hall/CRC: London, UK, 1984; p. 368. [[Google Scholar](#)]
53. Vapnik, V. The Nature of Statistical Learning Theory; Springer-Verlag: New York, NY, USA, 2000; p. 314. [[Google Scholar](#)]
54. Asadi, H.H.; Hale, M. A predictive GIS model for mapping potential gold and base metal mineralization in Takab area, Iran. *Comput. Geosci.* **2001**, *27*, 901–912. [[Google Scholar](#)] [[CrossRef](#)]
55. Mahvash Mohammadi, N.; Hezarkhani, A. Application of support vector machine for the separation of mineralised zones in the Takht-e-Gonbad porphyry deposit, SE Iran. *J. Afr. Earth. Sci.* **2018**, *143*, 301–308. [[Google Scholar](#)] [[CrossRef](#)]
56. Huang, C.; Davis, L.S.; Townshend, J.R.G. An assessment of support vector machines for land cover classification. *Int. J. Remote. Sens.* **2002**, *23*, 725–749. [[Google Scholar](#)] [[CrossRef](#)]
57. Burges, C.J.C. A tutorial on support vector machines for pattern recognition. *Data. Min. Knowl. Disc.* **1998**, *2*, 121–167. [[Google Scholar](#)] [[CrossRef](#)]
58. Zuo, R.; Carranza, E.J.M. Support vector machine: A tool for mapping mineral prospectivity. *Comput. Geosci.* **2011**, *37*, 1967–1975. [[Google Scholar](#)] [[CrossRef](#)]
59. Zaremotlagh, S.; Hezarkhani, A. The use of decision tree induction and artificial neural networks for recognizing the geochemical distribution patterns of LREE in the Choghart deposit, Central Iran. *J. Afr. Earth. Sci.* **2017**, *128*, 37–46. [[Google Scholar](#)] [[CrossRef](#)]
60. Celik, U.; Basarir, C. The prediction of precious metal prices via artificial neural network by using RapidMiner. *Alphan. J.* **2017**, *5*, 45. [[Google Scholar](#)] [[CrossRef](#)]

61. Brown, W.M.; Gedeon, T.D.; Groves, D.I.; Barnes, R.G. Artificial neural networks: A new method for mineral prospectivity mapping. *Aust. J. Earth. Sci.* **2000**, *47*, 757–770. [[Google Scholar](#)] [[CrossRef](#)]
62. Panda, L.; Tripathy, S.K. Performance prediction of gravity concentrator by using artificial neural network-a case study. *Int. J. Min. Sci. Technol.* **2014**, *24*, 461–465. [[Google Scholar](#)] [[CrossRef](#)]
63. Imamverdiyev, Y.; Sukhostat, L. Lithological facies classification using deep convolutional neural network. *J. Petrol. Sci. Eng.* **2019**, *174*, 216–228. [[Google Scholar](#)] [[CrossRef](#)]
64. Ghorbanzadeh, O.; Blaschke, T.; Gholamnia, K.; Meena, S.; Tiede, D.; Aryal, J. Evaluation of different machine learning methods and deep-learning convolutional neural networks for landslide detection. *Remote. Sens.* **2019**, *11*, 196. [[Google Scholar](#)] [[CrossRef](#)]
65. Sun, T.; Wu, K.; Chen, L.; Liu, W.; Wang, Y.; Zhang, C. Joint application of fractal analysis and weights-of-evidence method for revealing the geological controls on regional-scale tungsten mineralization in southern Jiangxi Province, China. *Minerals* **2017**, *7*, 243. [[Google Scholar](#)] [[CrossRef](#)]
66. Jiangxi Bureau of Geology and Mineral Resources. Mineral Prospecting and Targeting of W-Sn-Pb-Zn Deposits in Southern Jiangxi Province; Jiangxi Bureau of Geology and Mineral Resources: Nanchang, China, 2002; p. 112. (In Chinese) [[Google Scholar](#)]
67. Chen, X.; Fu, J. Geochemical Maps of Nanling Range; China University of Geoscience Press: Wuhan, China, 2012; p. 109. (In Chinese) [[Google Scholar](#)]
68. Xie, X.J.; Mu, X.Z.; Ren, T.X. Geochemical mapping in China. *J. Geochem. Explor.* **1997**, *60*, 99–113. [[Google Scholar](#)]
69. Xie, X.J.; Ren, T.X.; Xi, X.H.; Zhang, L.S. The Implementation of the regional geochemistry-National Reconnaissance Program (RGNR) in China in the past thirty years. *Acta Geosci. Sin.* **2009**, *30*, 700–716. (In Chinese) [[Google Scholar](#)]
70. Carranza, E.J.M. Objective selection of suitable unit cell size in data-driven modeling of mineral prospectivity. *Comput. Geosci.* **2009**, *35*, 2032–2046. [[Google Scholar](#)] [[CrossRef](#)]
71. Hengl, T. Finding the right pixel size. *Comput. Geosci.* **2006**, *32*, 1283–1298. [[Google Scholar](#)] [[CrossRef](#)]
72. Carranza, E.J.M.; Hale, M.; Faassen, C. Selection of coherent deposit-type locations and their application in data-driven mineral prospectivity mapping. *Ore. Geol. Rev.* **2008**, *33*, 536–558. [[Google Scholar](#)] [[CrossRef](#)]
73. Badel, M.; Angorani, S.; Shariat Panahi, M. The application of median indicator Kriging and neural network in modeling mixed population in an iron ore deposit. *Comput. Geosci.* **2011**, *37*, 530–540. [[Google Scholar](#)] [[CrossRef](#)]
74. Porwal, A.; Carranza, E.J.M.; Hale, M. Artificial neural networks for mineral-potential mapping: A case study from Aravalli Province, western India. *Nat. Resour. Res.* **2003**, *12*, 155–171. [[Google Scholar](#)] [[CrossRef](#)]
75. Xiong, Y.; Zuo, R. Effects of misclassification costs on mapping mineral prospectivity. *Ore. Geol. Rev.* **2017**, *82*, 1–9. [[Google Scholar](#)] [[CrossRef](#)]
76. Liu, C.; Berry, P.M.; Dawson, T.P.; Pearson, R.G. Selecting thresholds of occurrence in the prediction of species distributions. *Ecography* **2005**, *28*, 385–393. [[Google Scholar](#)] [[CrossRef](#)]

77. Tien Bui, D.; Tuan, T.A.; Klempe, H.; Pradhan, B.; Revhaug, I. Spatial prediction models for shallow landslide hazards: A comparative assessment of the efficacy of support vector machines, artificial neural networks, kernel logistic regression, and logistic model tree. *Landslides* **2015**, 13, 361–378. [[Google Scholar](#)] [[CrossRef](#)]
78. Nykänen, V.; Lahti, I.; Niiranen, T.; Korhonen, K. Receiver operating characteristics (ROC) as validation tool for prospectivity models—A magmatic Ni–Cu case study from the Central Lapland Greenstone Belt, Northern Finland. *Ore. Geol. Rev.* **2015**, 71, 853–860. [[Google Scholar](#)] [[CrossRef](#)]
79. Nykänen, V.; Niiranen, T.; Molnár, F.; Lahti, I.; Korhonen, K.; Cook, N.; Skyttä, P. Optimizing a knowledge-driven prospectivity model for gold deposits within Peräpohja Belt, Northern Finland. *Nat. Resour. Res.* **2017**, 26, 571–584. [[Google Scholar](#)] [[CrossRef](#)]
80. Tien Bui, D.; Ho, T.-C.; Pradhan, B.; Pham, B.-T.; Nhu, V.-H.; Revhaug, I. GIS-based modeling of rainfall-induced landslides using data mining-based functional trees classifier with adaboost, bagging, and multiboost ensemble frameworks. *Environ. Earth Sci.* **2016**, 75, 1101. [[Google Scholar](#)] [[CrossRef](#)]
81. Murphy, K.P. *Machine Learning: A Probabilistic Perspective*; The MIT Press: London, UK, 2012; p. 1096. [[Google Scholar](#)]
82. McKay, G.; Harris, J.R. Comparison of the data-driven random forests model and a knowledge-driven method for mineral prospectivity mapping: A case study for gold deposits around the Huritz Group and Nuelin Suite, Nunavut, Canada. *Nat. Resour. Res.* **2015**, 25, 125–143. [[Google Scholar](#)] [[CrossRef](#)]
83. Group of Tungsten Deposits in Nanling Range of Ministry of Metallurgy. *Tungsten Deposits in South China*; Metallurgical Industry Press: Beijing, China, 1985; p. 496. (In Chinese) [[Google Scholar](#)]
84. Fang, G.C.; Tong, Q.Q.; Sun, J.; Zhu, G.H.; Chen, Z.H.; Zeng, Z.L.; Liu, K.L. Stable isotope geochemical characteristics of Pangushan tungsten deposit in southern Jiangxi Province. *Miner. Depo.* **2014**, 33, 1391–1399. (In Chinese) [[Google Scholar](#)]
85. Xu, T.; Wang, Y. Sulfur and lead isotope composition on tracing ore-forming materials of the Xihuashan tungsten deposit in southern Jiangxi. *Bull. Miner. Petrol. Geochem.* **2014**, 33, 342–347. (In Chinese) [[Google Scholar](#)]
86. Lecumberri-Sanchez, P.; Vieira, R.; Heinrich, C.A.; Pinto, F.; Wälle, M. Fluid-rock interaction is decisive for the formation of tungsten deposits. *Geology* **2017**, 45, 579–582. [[Google Scholar](#)] [[CrossRef](#)]
87. Tan, Y.J. Composition characteristics and controlling factors of tungsten mineral of the endogenetic tungsten deposits in South China. *China Tungsten Ind.* **1999**, 14, 84–89. (In Chinese) [[Google Scholar](#)]