Dynamic Monitoring and Evaluation of Regional EE Quality Based on Multi-source Remote Sensing Data

Meng Li*

College of Resources, Environment, History and Culture, Xianyang Normal University, Xianyang, China

Abstract: *Regional EEal protection is an inevitable trend of environmental protection development. Based on multi-source remote sensing data, a typical land remediation project was selected. The rectification process of the project area. Monitoring and analysis. The results show that: 1) The humidity and greenness indicators have a positive impact on the ecological environment (EE) quality of the project area, and the dry heat index has a negative impact; 2) the average RSEI before repair, the middle and the back are 0.652, 0.572 and 0.605 respectively; RSEI fine grade level ratio of 78.73%, 39.55% and 63.29%; RSEI worse, better change, the ratio was 42.55%, 46.25% and 11.20%; 3) the EE quality in the project area showing the "first dropped and then rose to a total The trend of decline indicates that the "remediation period – the deterioration of the recovery period" has become better – the whole process is even worse. Land remediation will cause continuous disturbance to the EE of the project area, and there will be a lag period for restoring and improving the regional EE. After five years of construction, the EE quality level of the project area is still lower than the level before the remediation.*

Keywords: *Multi-source Remote Sensing Data; Regional EE; Dynamic Monitoring; SEI Model*

1. Introduction

With the rapid development of urbanization and industrialization, the contradiction between people and land has become increasingly prominent, and the pressure on land, resources and the environment is increasing. Land remediation plays an active role in ensuring national food security, supporting rural revitalization strategies, optimizing land resource allocation, and promoting ecological civilization construction. It has played an active role in stabilizing effective arable land, improving cultivated land production capacity, and optimizing land use structure. This role has become one of the largest organized human activities in China, changing land use patterns and affecting terrestrial ecosystems [1-4].

Land and resources are the material basis for green development, space carriers, energy and components. Under the goal of ecological civilization construction, China's land consolidation will gradually shift from increasing the amount of cultivated land to focusing on the quantity protection, quality protection and ecological protection of cultivated land. [5]. The "National Land Rehabilitation Plan" clearly stipulates that "in accordance with the requirements of ecological civilization construction, the implementation of landscape forest lake comprehensive improvement, strengthening EEal protection and restoration, and vigorously building ecological land." "Strengthening ecological construction" security barriers, strengthening farmland ecological protection and construction to carry out the demonstration and construction of land EE remediation as the main goal and important task, and strive to promote the EE construction of land remediation.

EE quality monitoring and evaluation is the basis for analyzing the benefits of land spatial planning and land remediation, but due to its rich connotation and multi-source performance, complex mechanisms, scale differences and spatio-temporal changes [6-7] it has become an administrative and scientific research difficult. On the regional scale, methods for evaluating the quality of EE include analytic hierarchy process [6], comprehensive index method [8], fuzzy comprehensive evaluation method [9] and coefficient of variation method [10]. However, a unified normative evaluation system has not yet been formed. In 2006, the former State Environmental Protection Administration issued the "Technical Specifications for EE Assessment (Trial)", which proposed EE indicators as the basis for regional EE evaluation and evaluation. Later, the EE assessment was revised. With the deepening of the application of remote sensing technology, the EE assessment method has been continuously improved

ISSN 2616-5872 Vol.4, Issue 1: 5-12, DOI: 10.25236/AJEE.2022.040102

[11-12]. Xu Hanqiu [13] proposed remote sensing ecological indicators with reference to the above specifications. Using remote sensing data to achieve rapid monitoring of regional EE. At the project level, scholars use different methods to assess and analyze the impact of land remediation on the EE based on different perspectives. Overall assessment and local single factor assessment. The macro overall assessment is based on landscape ecology [14], ecosystem services [15] and land consolidation planning [16], and the land improvement project area as an ecosystem; the local single factor assessment mainly selects the ecosystem. Key elements such as carbon [17-18] and nitrogen [19-20] were evaluated; monitoring methods include comprehensive index method, multi-factor comprehensive evaluation method, correlation analysis method, entropy weight matter element promotion model, cloud model and so on. In general, at the project level, eco-environment monitoring is based primarily on statistical data or land-use data, using a comprehensive index approach. For a period of time after the implementation of the project, the objectives of the research scope, the objectivity of the data source and the validity of the evaluation indicators are qualitative and semi-quantitative analysis of the sexual and procedural aspects, as well as improved monitoring and evaluation.

Continuously monitor and dynamically assess the quality of the EE. Based on multi-source remote sensing data, this paper selected a typical land restoration project that uses Landsat-5TM and Landsat-8 OLI/TIRS image data to prioritize and repair basic geographic data. After the repair and the post-repair period. Project construction data, coupled humidity and green. According to the index of degree, heat and dryness, the RSEI model is constructed through principal component analysis to realize the dynamic monitoring and evaluation of the EE.

2. Roposed Method

2.1 Multi-Source Remote Sensing

With the development of remote sensing technology, a large number of different optical observation satellite sensors, such as optical, thermal infrared and microwave, collect multiple remote sensing image data (multiphase, multispectral, multi-sensor, multi-platform and multi-resolution) in the same field. The more you come, the more multi-source remote sensing.

Compared with single-source remote sensing image data, the information provided by multi-source remote sensing image data is redundant, complementary, and synergistic. Redundancy of multi-source remote sensing image data indicates that they have the same representation or description of the environment or target; complementarity means that the information comes from different degrees of freedom and is independent of each other; cooperative information refers to different sensors that observe and process information. Rely on other information. In remote sensing, data fusion belongs to a kind of attribute fusion. It intelligently synthesizes multi-source remote sensing image data in the same region, resulting in more accurate, complete and reliable estimation and judgment than a single source. The advantage is the robustness of operation, the improved spatial resolution and image clarity, improve the accuracy of the planar mapping, classification accuracy and reliability, enhanced dynamic monitoring and interpretation functions to reduce ambiguity, improve remote sensing image data. Utilization rate, etc.

The form of multi-source remote sensing information can be divided into two levels: pixel level (before feature extraction), feature level (before attribute description), and decision level (after sensor data independent attribute description). Therefore, information fusion can be carried out on three levels: at the pixel level, feature level and decision level, three low integration fusion frameworks are formed. Pixel-level information fusion: This is the lowest level of information fusion that can be performed on a pixel or resolution unit, also known as data-level fusion, which includes one-dimensional time series data and focal plane data. The spatially-registered remote sensing image data is directly fused, and then the feature extraction and attribute description of the fused data are performed. The advantage of pixel-level fusion is that it retains as much information as possible and has high precision. The downside is that it handles a lot of information, which is time consuming and poorly real time. Feature Level Information Fusion: A single sensor performs only target detection and feature extraction processing. Prior to target classification, target information or filtered trajectories from multiple sensors are combined into a multi-source integration (MSI) trajectory, and feature extraction is then performed to generate feature vectors. When the combination of these eigenvectors, based on feature-level fusion process Bayes decision method, neural network method, and performing a feature vector-based fusion properties described. The advantage is that a large amount of information compression can be realized, it is convenient for real-time processing, and provides functions directly related to decision analysis, so

ISSN 2616-5872 Vol.4, Issue 1: 5-12, DOI: 10.25236/AJEE.2022.040102

the result of the fusion maximizes the feature information required for decision analysis. At present, most research on fusion systems is carried out at this level. The disadvantage is that the fusion accuracy is worse than the pixel level. Decision-level information fusion: This is the highest level of convergence. Each sensor first completes the classification of the target and combines another classification decision to generate a complete decision. Therefore, for the target, at least two sensors must be detected and classified simultaneously prior to sorting.

2.2 The Selection of Evaluation Indicators

Whether the selection evaluation is reasonable or not has a significant impact on the EE evaluation results. It is hoped that the selection of evaluation indicators is as small as possible and the evaluation results are as accurate as possible. Therefore, the selection of evaluation indicators should follow the following five principles: (1) Science: Evaluation indicators should be based on scientific definitions, and their changes should be related to changes in EE, reflecting the current status and trends of EE. surroundings. Geological environment. (2) Independence: There are many factors that affect EE, and the contribution rate of each factor is also different. (3) The rationality of the time-space scale: the time-space resolution index must be as consistent as possible, reflecting the status and characteristics of regional energy efficiency. (4) Overall: According to the conceptual model, the corresponding indicators can be selected to fully reflect the current status and changes of regional energy efficiency. (5) Accessibility: The selected indicators should be obtained through remote sensing data as much as possible. These indicators have clear meanings for qualitative or quantitative analysis. According to the actual energy efficiency and year changes in the Qinghai Lake basin, 9 vegetation coverage, temperature, vegetation drought index, net primary productivity, land type, surface temperature, annual rainfall, digital elevation model, slope and wind speed are selected. index. These factors have different driving forces for the changes in energy efficiency in the Qinghai Lake Basin. Climate factors mainly include TVDI, annual rainfall, etc. Terrain factors include DEM and slope. The dynamic change of land cover type is a lateral reflection of the impact of human production activities on energy efficiency; vegetation cover is a “rule”. Using ground satellite data, it is possible to quickly obtain the ecological evaluation indicators specified by the wind turbine. The evaluation unit is the smallest precise area in the ecological environment evaluation process. Whether the selection of evaluation unit is reasonable has a certain impact on the results of EE evaluation.

In practical applications, the evaluation unit mainly combines the accuracy of index data with the specific needs of people. (1) Grid/Grid Element: For the surface grid division of the evaluation area, squares are usually used as the evaluation unit. Through reprojection and resampling, data with no spatial scale can be obtained. (2) Administrative unit: the vector scope of the administrative division is the evaluation unit, and the county and city level is the evaluation unit. These evaluation units have abundant natural and economic conditions, and the common data source is statistical yearbook data. The scope of administrative units is relatively fixed and the structure is incomplete. (3) Watershed unit: The watershed maintains the integrity of the ecosystem to a large extent. The traditional method of collecting watershed data is mainly based on statistical data. The area of the basin is generally large, and the individual indicators in different regions of the basin are quite different.

2.3 Research Ideas

Land remediation is a process of reorganizing and re-optimizing land resources and their utilization methods. According to different restoration stages, the comprehensive construction schedule, land use methods, and land management methods of the project construction content have many direct impacts on the environment. In terms of soil factors, the implementation of land improvement projects and agricultural production will affect the physical and chemical properties of soil, soil biological activity, etc., change soil moisture, soil temperature and texture, and affect soil fertility and soil. In terms of water resources, the implementation of land remediation projects and the use of facilities will affect local water resources allocation, improve water use efficiency, improve water resources management and other activities, and may cause soil erosion. The EE quality dynamic detection process is shown in Figure 1.

ISSN 2616-5872 Vol.4, Issue 1: 5-12, DOI: 10.25236/AJEE.2022.040102

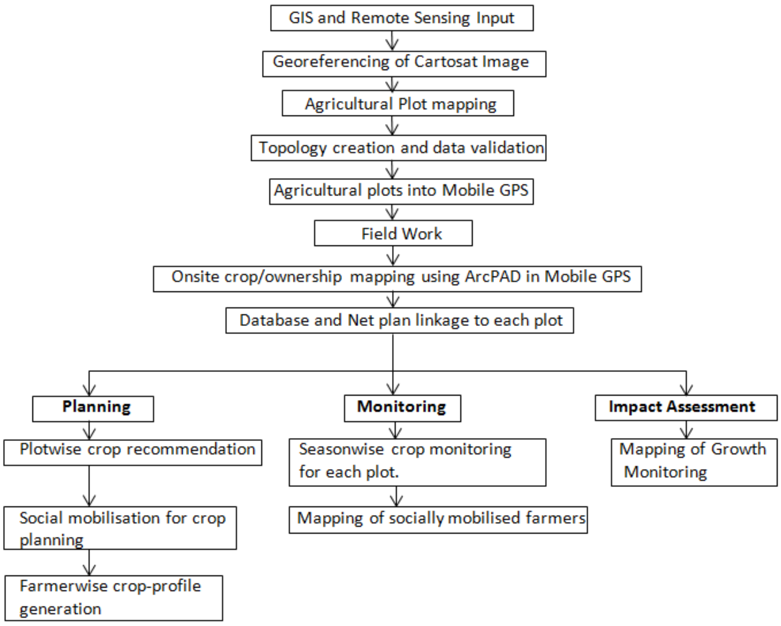

Figure 1: E quality dynamic testing process

$$\begin{aligned} WET_{(TM)} &= 0.0315\rho_{blue} + 0.2021\rho_{green} + 0.3102\rho_{red} \\ &+ 0.5194\rho_{NIR} - 0.6806\rho_{SWIR1} - -0.6109\rho_{SWIR2} \end{aligned} \quad (1)$$

$$\begin{aligned} WET_{(OLI)} &= 0.1511\rho_{blue} + 0.1792\rho_{green} + 0.3283\rho_{red} \\ &+ 0.3407\rho_{NIR} - 0.7117\rho_{SWIR1} - -0.4559\rho_{SWIR2} \end{aligned} \quad (2)$$

Herein to characterize the present NDVI greenness index, calculated, see formula (3).

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \quad (3)$$

This article describes the thermal index through the inversion of surface temperature. The steps are as follows:

1) The gray value of the pixels in the TM6Landsat5 frequency band is converted into the radiation value (L6) on the sensor. Use a specific surface emissivity (ε6) to convert into actual surface temperature (LST). The calculation methods are described in formulas (4), (5), and (6).

$$L_6 = gain \bullet DN + bias \quad (4)$$

$$T_b = K_2 / ln(K_1 / K_6 + 1) \quad (5)$$

$$LST = T_b / \left[1 + (\lambda T / \alpha) ln\,\varepsilon_6\right] \quad (6)$$

2) In the infrared band Landsat82, the land surface temperature 10 selects the band inversion to scale the thermal infrared radiation radiation value (L 10), which contains three components. The calculation method of thermal infrared radiation value is shown in formula (7) and formula (8).

$$L_{10} = \tau_{10}\left[\varepsilon_{10} B_{10}(T_s) + (1-\varepsilon_{10}) I_{10}^{\downarrow}\right] + I_{10}^{\uparrow} \quad (7)$$

$$B_{10}(T_s) = \left[L_{10} - I_{10}^{\uparrow} - \tau_{10}(1-\varepsilon_{10}) I_{10}^{\downarrow}\right] / \tau_{10}\varepsilon_{10} \quad (8)$$

The surface real temperature (LST) is obtained by Planck's law, and the formula is given by equation (9).

$$LST = K_2 / ln(K_1 / B_{10}(T_s) + 1) \quad (9)$$

In the formula, K1 and K2 are calibration coefficients, which are obtained from image metadata.

ISSN 2616-5872 Vol.4, Issue 1: 5-12, DOI: 10.25236/AJEE.2022.040102

The building index and the bare soil index are used to synthesize the dryness index and record it as the dryness index (NDBSI). The calculation method is shown in formula (10).

$$NDBSI = (SI + IBI) / 2 \quad (10)$$

3. Experiments

This study selected a high-standard farmland construction project as a research case. The project area belongs to the mid-subtropical zone - the north subtropical seasonal monsoon humid climate, with sufficient sunshine, cold winters, hot summers and four distinct seasons; annual average temperature of 16.8 ℃, annual precipitation of 1340 mm, annual frost-free period of about 281 days; project area Kaiping, average 25 meters above sea level. The agricultural production in the project area is mainly based on food crops, mainly planting double-season rice; other cash crops, mainly cotton and rapeseed. The project construction scale is 2876.66hm2, with a total investment of 85.411 million yuan. The implementation period is 2016-2018. The project involves 12 administrative villages with an area of 217.45hm2 of arable land, an area of 309.80hm2 of land leveling works, and an excavation area of 311800m3. New irrigation transformation channels, drainage channels and drainage channels 264.23km, pipelines culvert 4548, and reservoirs 180. There are 180 new pumping stations, 60 mechanical growth bridges, and 1.41km transmission lines; 297.44 kilometers of new roads and 173.81 kilometers of production roads. "The featured method has achieved agricultural benefits and increased farmers' income.

4. Discussion

Perform PCA transformation on the synthesized new image to obtain the principal component analysis results, as shown in Table 1. The results show that the first principal components of the 13 stages are 62.99%, 72.70%, and 66.89% respectively. The signs and amplitudes of other principal component indicators are unstable, and the interpretation of the results is weak. This is only the first time the principal component model has been established. Corresponding to the calculation results of environmental quality, use 1-PC1 RSEI0 to get the initial ecological index, and then normalize RSEI0 to get the RSEI index. The remote sensing evaluation of EE quality is shown in Figure 2.

Table 1: Principal component analysis results

index	PC1	PC 2	PC 3	PC 4
WET	0.520	0.257	0.545	0.606
NDVI	0.264	0.695	0.462	0.484
LST	0.440	0.595	0.672	0.026
NDBSI	0.683	0.311	0.197	0.631
Eigenvalue (RSEI)	0.098	0.030	0.016	0.002
Percent Eigenvalue%	66.89	20.59	11.26	1.26

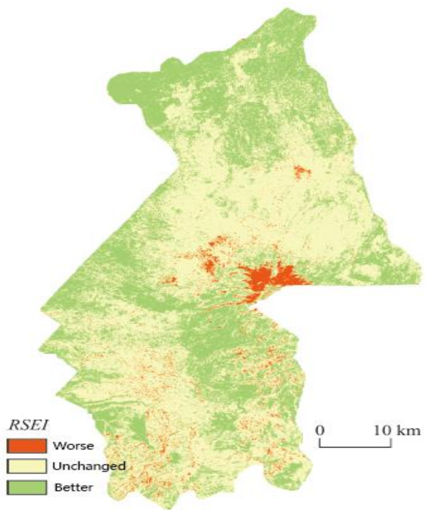

Figure 2: Remote sensing evaluation of EE quality

ISSN 2616-5872 Vol.4, Issue 1: 5-12, DOI: 10.25236/AJEE.2022.040102

Based on three stages of remediation period (pre-remediation-remediation), recovery period (after remediation-remediation) and whole process (before remediation-remediation), 5 levels of RSEI (poor, poor, medium, good, Excellent) The grade difference is divided into four grades and four grades according to the change of each grade to other grades, which are classified into three grades and nine grades. 2 grade difference: grade range [4, 4]; the change range of each adjacent two grades is grade 1 (and so on), the negative value is high-grade to low-level change, the EE quality is deteriorated, and the zero value indicates that the EE quality remains unchanged. Change, positive values indicate that the quality of the EE is getting better, as shown in Fig 3.

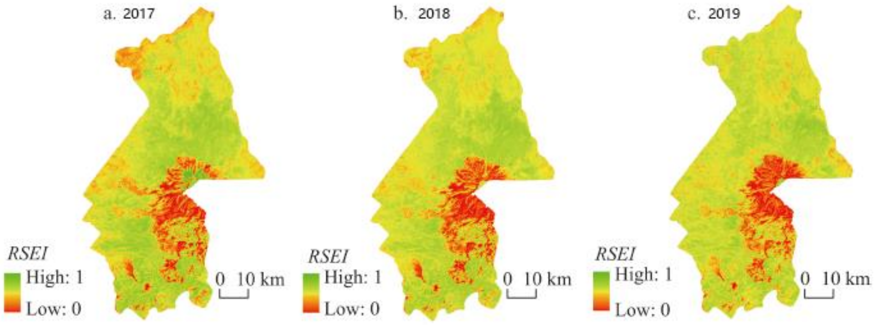

Figure 3: Evaluation of EE quality before and after remediation

Changes in various components: the humidity index continued to rise before, during and after the recovery; the green index decreased slightly and then improved; the heat index increased significantly and then decreased. According to the results of field surveys, the types of crops before, during and after the project area remain basically unchanged, but the output has changed. Before, after and after the restoration, the double-cropping rice and the average yield per mu were 11,100 and 10,950, respectively. At the same time, improve the supporting projects in the irrigation area to improve the stability of agricultural production; increase the impermeability of bridges, culverts, pumping stations and other infrastructure. This situation in the region confirmed the changes in indicators such as NDVI, WET, LST and NDBSI. The EE quality is shown in Figure 4.

Figure 4: EE quality map

From the perspective of space, according to the research results, UAV image recognition and on-site research, the regions with different EEs at different stages are mainly distributed between facilities and villages. The areas with large changes in the EE are mainly distributed by equipment. Regional and agricultural land reflects the negative impact of project implementation and prevention of environmental quality leakage in the project area.

ISSN 2616-5872 Vol.4, Issue 1: 5-12, DOI: 10.25236/AJEE.2022.040102

5. Conclusion

The project area has been restored for 6 years. Analyze the changes in EE quality during the entire repair process. The results show that: 1) The humidity and greenness indicators of the project area are positively correlated with the EE quality of the project area, the dry heat index is negatively correlated, and the drought index is the most significant. 2) The areas with good RSEI before, after and after restoration accounted for 78.73%, 39.55%, and 63.29% of the restoration, restoration, and whole process stages, respectively. The main changes in RSEI have become worse, better, and unchanged. The corresponding proportions are 62.48%, 44.39% and 46.25% respectively. 3) The energy efficiency quality of the project area "decreased first and then increased-overall decline", expressed as "deterioration in the recovery period-long recovery period-deterioration in the whole process". Land improvement has caused continuous disturbance to the energy efficiency of the project area, and there is a lag in the restoration and improvement of regional energy efficiency. During the restoration period, the project facilities will benefit, the regional irrigation support rate will increase, crop growth conditions will be improved and improved, and the ecological environment quality will be restored. In general, the quality of the ecological environment in the project area first declined and then increased, but the quality of the ecological environment after restoration was lower than the quality of the ecological environment before restoration, mainly due to the production roads after construction.

References

[1] Zhang, L., Zhang, L., & Bo, D. (2016). Deep learning for remote sensing data: a technical tutorial on the state of the art. IEEE Geoscience & Remote Sensing Magazine, 4(2), 22-40.
[2] Dardel C, Kergoat L, Hiernaux P, et al. Re-greening Sahel: 30 years of remote sensing data and field observations (Mali, Niger)[J]. Remote Sensing of Environment, 2014, 140(140):350-364.
[3] Cracknell, M. J., & Reading, A. M. (2014). Geological mapping using remote sensing data: a comparison of five machine learning algorithms, their response to variations in the spatial distribution of training data and the use of explicit spatial information. Computers & Geosciences, 63(1), 22-33.
[4] Luo, Y., Zheng, X., Zhao, T., & Chen, J. (2014). A climatology of aerosol optical depth over china from recent 10 years of modis remote sensing data. Ecology & Environmental Sciences, 34(3), 863-870.
[5] Wei, W., Xiao, P., Feng, X., Li, H., Ma, R., & Duan, H., et al. (2014). Monitoring lake changes of qinghai-tibetan plateau over the past 30 years using satellite remote sensing data. Chinese Science Bulletin, 59(10), 1021-1035.
[6] Kussul, N., Lavreniuk, M., Skakun, S., & Shelestov, A. (2017). Deep learning classification of land cover and crop types using remote sensing data. IEEE Geoscience & Remote Sensing Letters, PP(99), 1-5.
[7] Aizen, V. B., Kuzmichenok, V. A., Surazakov, A. B., & Aizen, E. M. (2017). Glacier changes in the central and northern tien shan during the last 140 years based on surface and remote-sensing data. Annals of Glaciology, 43(1), 202-213(12).
[8] Douaoui, E. K., Abd, NICOLAS, Hervé, WALTER, & Christian. (2017). Detecting salinity hazards within a semiarid context by means of combining soil and remote-sensing data. Geoderma, 134(1-2), 0-230.
[9] Lin, C., Ying, L., Yuan, Z., Lau, A. K. H., Li, C., & Fung, J. C. H. (2015). Using satellite remote sensing data to estimate the high-resolution distribution of ground-level pm 2.5. Remote Sensing of Environment, 156, 117-128.
[10] CAMMALLERI, ANDERSON, M., C., GAO, HAIN, & C., R., et al. (2014). Mapping daily evapotranspiration at field scales over rainfed and irrigated agricultural areas using remote sensing data fusion. Agricultural & Forest Meteorology, 186(10), 1-11.
[11] Joshi, N., Baumann, M., Ehammer, A., Fensholt, R., Grogan, K., & Hostert, P., et al. (2016). A review of the application of optical and radar remote sensing data fusion to land use mapping and monitoring. Remote Sensing, 8(1), 70-74.
[12] Shen, H., Li, X., Cheng, Q., Chao, Z., Gang, Y., & Li, H., et al. (2015). Missing information reconstruction of remote sensing data: a technical review. IEEE Geoscience & Remote Sensing Magazine, 3(3), 61-85.
[13] Tuia, D., Persello, C., & Bruzzone, L. (2016). Domain adaptation for the classification of remote sensing data: an overview of recent advances. IEEE Geoscience & Remote Sensing Magazine, 4(2), 41-57.
[14] Alsharif, A. A. A., & Pradhan, B. (2014). Urban sprawl analysis of tripoli metropolitan city (libya) using remote sensing data and multivariate logistic regression model. Journal of the Indian Society of

ISSN 2616-5872 Vol.4, Issue 1: 5-12, DOI: 10.25236/AJEE.2022.040102

Remote Sensing, 42(1), 149-163.

[15] Ali, I., Greifeneder, F., Stamenkovic, J., Neumann, M., & Notarnicola, C. (2015). Review of machine learning approaches for biomass and soil moisture retrievals from remote sensing data. Remote Sensing, 7(12), 221-236.

[16] Lu, Z., Im, J., Rhee, J., & Hodgson, M. (2014). Building type classification using spatial and landscape attributes derived from lidar remote sensing data. Landscape & Urban Planning, 130(1), 134-148.

[17] Schnebele, E., Cervone, G., Kumar, S., & Waters, N. (2014). Real time estimation of the calgary floods using limited remote sensing data. Water,6(2), 381-398.

[18] Yan, M., Wang, L., Peng, L., & Ranjan, R. (2015). Towards building a data-intensive index for big data computing - a case study of remote sensing data processing. Information Sciences, 319(C), 171-188.

[19] Li,ai Wang, Zhou, X., Zhu, X., Dong, Z., & Guo, W. (2016). Estimation of biomass in wheat using random forest regression algorithm and remote sensing data. Crop Journal, 4(3), 212-219.

[20] Ghamisi, P., Souza, R., Benediktsson, J. A., Xiao, X. Z., Rittner, L., & Lotufo, R. A. (2016). Extinction profiles for the classification of remote sensing data. IEEE Transactions on Geoscience & Remote Sensing,54(10), 5631-5645.