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Application of remote sensing techniques in lithology identification in Almeria

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Abstract. Remote sensing is emerging as an important method of information extraction in the field of lithology identification as a technology that can provide a cost-effective way of detecting and monitoring the physical characteristics of an area. This paper uses remote sensing techniques for lithology identification in Almeria, discusses the flaws and applicability of remote sensing techniques, and proposes a combined remote sensing approach. The lithological results identified by remote sensing indicate that northern Almeria is dominated by metamorphic and carbonate rock and the southern part is predominantly mafic rocks and felsi rocks. The identification results in Almeria from remote sensing imagery synthesised using Landsat-8 multiple band sets differ from actual lithology distribution. It shows the limitations of remote sensing techniques for lithology identification. Based on the limitations of remote sensing techniques demonstrated in the case study, this paper discusses how remote sensing improves the identification and analysis of lithology in other research cases by means of technical improvements combined with other techniques.

Keywords: Lithology identification, Remote Sensing Techniques, Almeria.

1. Introduction

Lithology is the sum of characteristics such as a rock's colour, composition, structure and tectonics, and lithology identification is the process of recognising and differentiating lithology through specific methods. Lithology identification is the process of classifying reservoir rocks into different units, sediments that have undergone similar geological conditions and diagenetic alterations. Accurately identifying lithology is a prerequisite for accurately determining porosity and oil saturation, as well as the basis for reservoir characterisation, reserve calculation, and geological modelling. It provides specific geological information for regional geological characterisation, a solid foundation for mining microscopic information such as ore types and grades, and the acquisition of macroscopic understanding of the transport status of rocks and ores under complex tectonics. It also provides credible indications of mineralisation, good target area predictions in conjunction with mineralisation theories and models, and strong evidence for later reserve estimation and 3D modelling.

The main methods of lithology identification are remagnetisation, logging, seismic, remote sensing, electromagnetic, geochemical, hand specimen and thin section analysis methods. The theoretical basis of remagnetic lithology identification is to analyse the characteristics and logical relationship between the combination of magnetisation and density for different lithologies by means of density and magnetisation scatter diagrams. Logging and seismic lithology identification are the most commonly

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used lithology identification methods in oil and gas exploration because of their large detection depth and relatively high vertical resolution. The geological information from the logging data is an important basis for determining a formation's oil-bearing reserves and formulating an exploitation plan. Seismic lithology identification is a way to determine the rock interface's depth and shape and understand the subsurface geology.

Remote sensing lithology identification technology is based on the continuous progress of spatial information technology, large-scale regional geological mapping and the increasing demand for modern 3s technology. The development of remote sensing technology is based on the continuous progress of spatial information technology and the increasing demand of modern 3s technology. The unique spectral advantages of remote sensing technology, combined with field verification tools for lithological mapping, have made it possible to carry out rapid and accurate large-scale geological mapping. The remote sensing technique is an effective way to quickly and accurately carry out large-scale geological mapping, and is also a new technique for carrying out modern geological mapping. It is also one of the new technologies and methods for modern geological mapping.

Therefore, this paper uses remote sensing techniques for lithology identification in Almeria, discusses the flaws and applicability of remote sensing techniques, and proposes a combined remote sensing approach.

2. Case study

2.1. Background

Almeria is located in south-eastern Spain. The area is at a plate boundary, so it is not homogeneous in terms of rock type. The area is affected by a semi-arid climate with sparse vegetation, which has little impact on remote sensing imaging (Figure 1).

Figure 1. Satellite map of Almeria.

2.2. Data and methods

In this case study, the 2017 Landsat-8 dataset for the area was downloaded from the USGS. After importing the data into QGIS, three bands were selected for pseudo-colour synthesis to highlight information about the target lithology. Bands, including bands5, bands3, and bands1, with high information content and low inter-band correlation, were selected for synthesis (Figure 2).

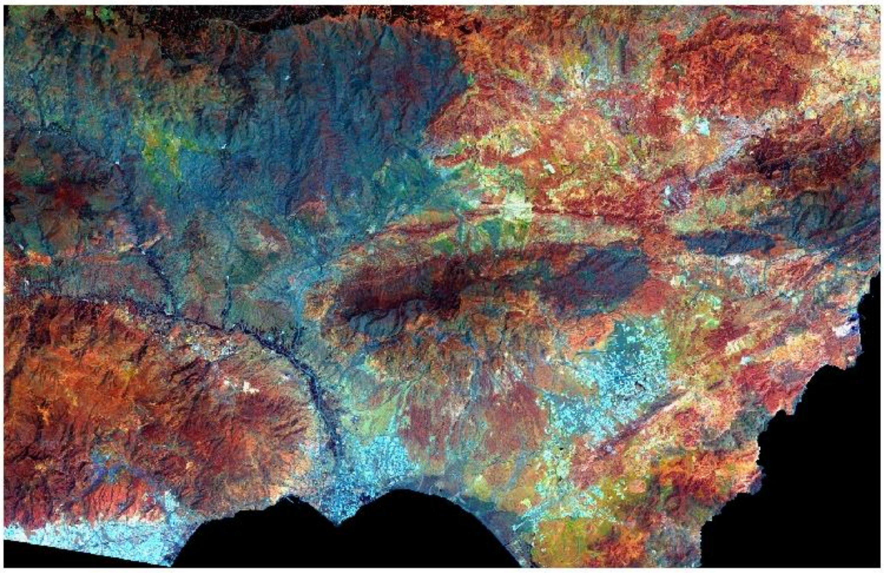

Figure 2. Synthetic false colour maps of Almeria (R: Band5, G: Band3, B: Band1)2.3 Results and discussion.

In Figure 3, the large blue area is at a relatively high altitude (800-1000m above sea level). This is the core of the Sierra de Alhamilla mountain range. The rocks in this area are of metamorphic origin and are very dark in colour with low albedo. It is initially identified as a dark metamorphic rock, mica schist or amphibolite. The surrounding reddish-brown rocks have the signature of carbonates. Presumed to be marble and metamorphic dolomite (dolomitic marble). The blocky texture with small patches of blue shows that dolomites are broken up and intercalated with schists.

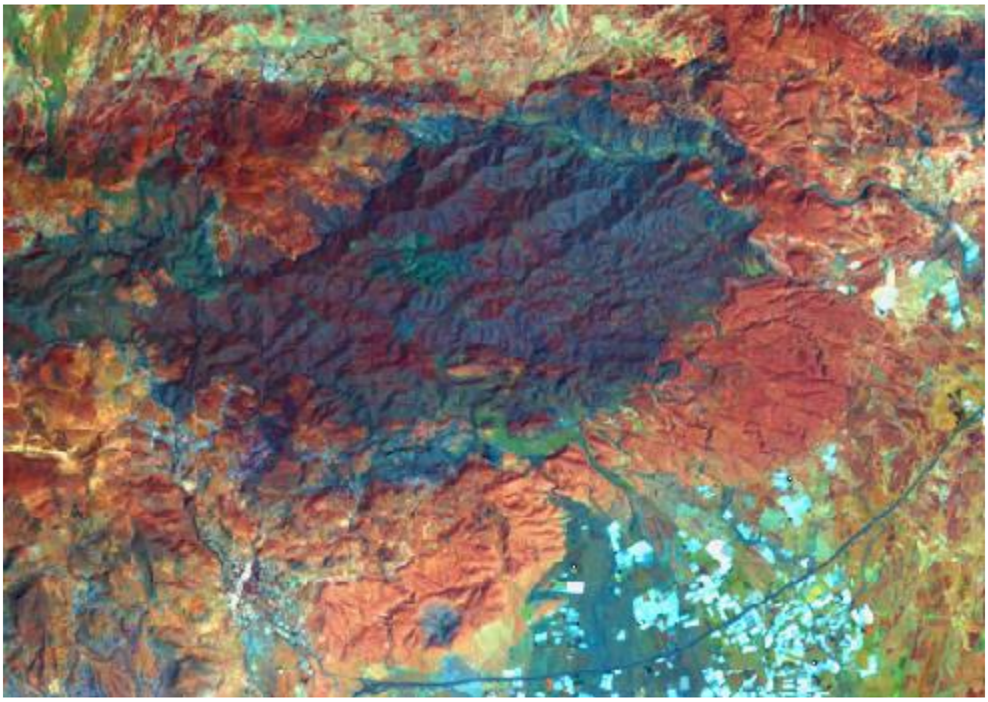

Figure 3. Interpreted synthetic false colour maps of Almeria (Northern part).

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In Figure 4, there are two main lithologies. The green part tends more towards smectite and the red-orange part more towards feldspathic. Smaller patches of feldspar within the predominantly dark dolomite patches. The the area is closer to orange, the more feldspathic the lithology tends to be.

In order to analyse the correctness and validity of remote sensing lithology identification by this method, the difference map were produced by comparing the false colour map with the actual lithology distribution map (Figure 5,6). In the difference map, the areas where the lithology has been correctly identified are marked blue, the areas where the spectrum does not yield a unique determination of lithology are marked green, the areas where the identification does not match the reality are marked yellow, and the areas where the lithology cannot be identified because of artefactual cover are marked red (Figure 6).

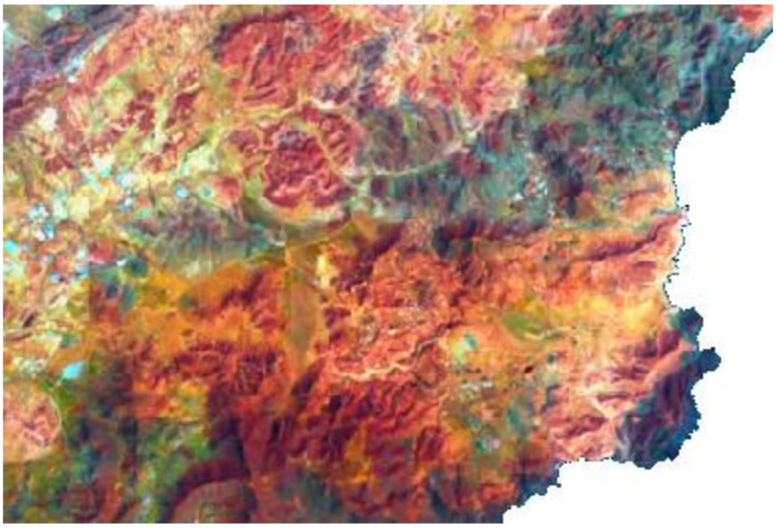

Figure 4. Interpreted lithology distribution map based on synthetic false colour maps of Almeria (Southern part).

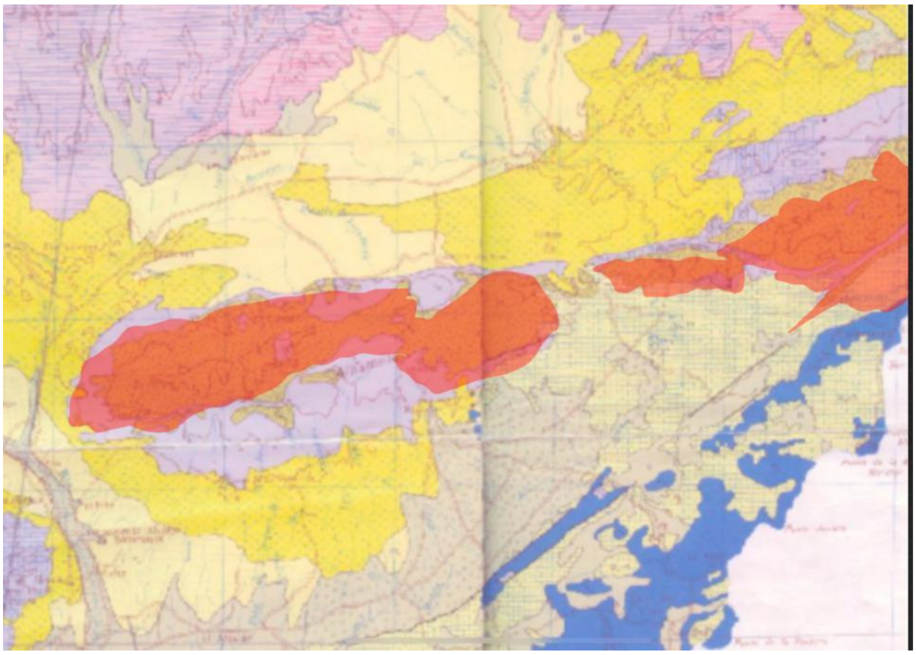

Figure 5. Lithology distribution map of Almeria.

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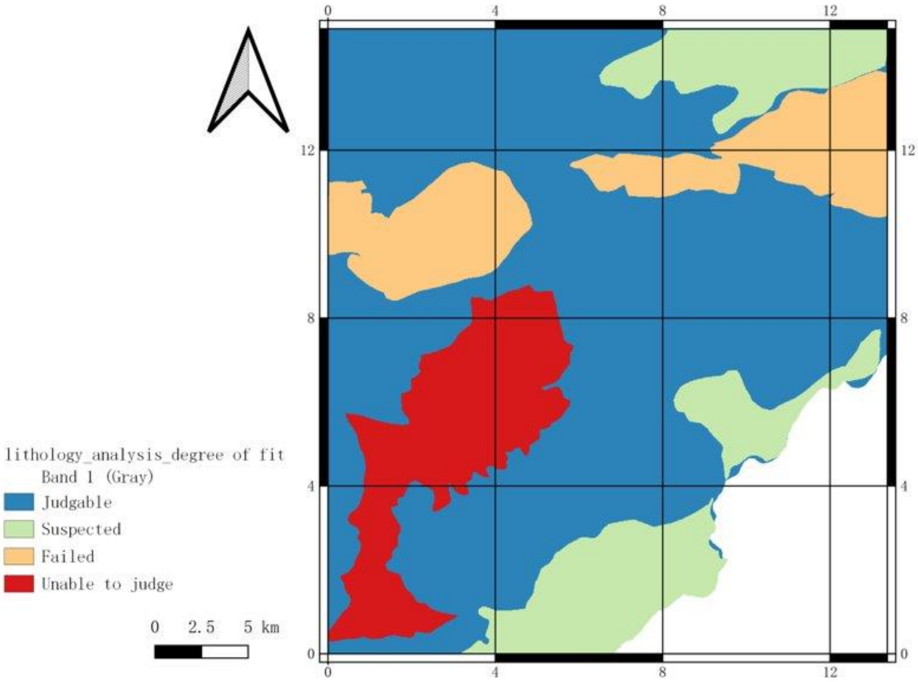

Figure 6. Difference between remote sensing identification map and lithology distribution map in Almeria.

The lithology cannot be identified in some areas due to obscuration by vegetation and artifacts. The similar spectrum does not match a unique lithology, although in some areas, there is no interference from land cover. In the northern part of the study area, the lithology identification results derived from remote sensing do not correspond to the actual lithology distribution. Compared to the lithology maps (Figure 4,5) from the field exploration, there are large errors between the lithology maps identified by remote sensing and the actual lithology distribution in some areas.

A preliminary false colour map from a single data source (Landsat-8) cannot provide reliable corroboration for lithology identification (Figure 2). In order to obtain accurate and reliable lithology identification results, a more accurate and effective remote sensing data process method should be considered. The introduction of multiple data sources that can be jointly incorporated into the determination of lithology identification is also a method that can improve the accuracy of lithology identification.

3. Application of remote sensing in lithology identification

3.1. Multispectral remote sensing lithological information extraction

Multispectral data covers a large spectral interval with a low spectral resolution, which cannot fully represent the spectral characteristics of the features. Multispectral remote sensing lithology recognition is mainly based on the spatial grayscale characteristics of the image, and the transformation method is used to enhance the difference of hue, colour, and texture of the image, as well as to extract texture information, or to use the method of multi-source data fusion to achieve the purpose of lithology recognition.

3.1.1. Enhanced Transformation. The use of enhanced transformation processing to extract tonal information can amplify the grey-scale differences between different lithologies, highlight the target information and improve the effectiveness of the image, thus improving the discriminatory ability of the

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interpreted sign. Nahid et al. used Aster731 (RGB) band combinations and band ratio images (RGB4/5-3/1-3/4) to better identify different lithological units and structures [1]. The TM3/1 (Y), 2/3(M) and 7/5 (C) ratio colour composite images with band ratio enhancement and the TIMS234 (RGB) colour composite images with decorrelation extension enhancement were considered to be better for the identification of different sedimentary rocks [2]. Jin et al performed principal component analysis on the TIMS data, where different features, due to their different radiometric properties, were distinguished by different principal component vectors. Then the PCI34 was superimposed and de-correlated with the 237 band of the original image respectively, enhancing the differences in lithological fine emissivity [3]. Mars used the correlation band absorption depth analysis (RBD) technique to identify clay, carbonate, and MgOH minerals based on strong absorption feature spectra in the bands 2.20 μm and 2.33 μm [4]. Rowan et al. were able to identify chert and dolomite using the visible NIR and short-wave IR bands of Aster data with matched filtering, and quartz-like rocks and carbonate rocks could be easily identified using the thermal IR band [5].

3.1.2. Texture information extraction. The grey-scale values of each lithological unit have their spatial variation, which is the basis for lithological classification using texture. Commonly used methods for extracting texture information include the grey-scale co-occurrence matrix, wavelet, and Fourier transform. Many scholars have shown that the involvement of texture information in classification significantly affects the improvement of lithology identification and classification accuracy.

Huang et al. used the classical variational function to calculate the texture information of TM6 bands, and together with the multispectral bands, the classification accuracy was improved from 40.16% to 72.66% when only multispectral bands were used [6]. Li used Aster data for lithology classification, and obtained the highest classification accuracy of 72.21% using only the original image and 76.55% by extracting the texture of visible to near-infrared bands with the original image using the variance function [7]. Zhao et al. used fractal-based textures for lithology classification and achieved better results [8]. Jiang et al. established a method to analyse textures using the IBm (fractional Brownian motion) model, which can identify carbonate rocks, clastic clay rocks, and the two interlayer [9].

3.1.3. Multi-source data fusion. Multi-source data fusion is an important method for remote sensing information extraction, which includes the fusion between different types, different accuracy and timely phase remote sensing data, as well as the fusion of remote sensing data and non-remote sensing data (such as DEM data, slope images, geochemical data, geophysical data). The fused data contains information of multiple data, which is beneficial to show the differences between different lithologies.

Rowan et al. used the standardised colour technique (CNT) to fuse Aster data with Radarsat data, and the fused image contains both the spectral information of Aster data and the topographic morphological features of Radarsat data, which enhances the lithological mapping capability [5]. The Aster data and DEM data are used to generate 3D remote sensing images, which can effectively identify the lithological units of Nile Canyon. Ma et al. used multi-source data to extract lithological information in areas with high vegetation cover, firstly finding out the relationship between different vegetation trace elements and spectral response, then combining multiple non-remote sensing data, establishing the correlation between composition, spectrum, and band for suitable TM band selection, and finally applying the weak information extraction method of remote sensing data for lithological classification, achieving better results [10]. Zhang used remote sensing and aerial radioactive information integration for lithology identification research [11].

The study of lithology identification using remote sensing and airborne radiological information combines the spectral and spatial texture information in remote sensing images, and the lithology identification energy spectrum signatures of radiological information. This shows that the multi-source data fusion method has broadened the application field of remote sensing and improved the application capability of remote sensing, which has a broad prospect.

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3.2. Hyperspectral remote sensing lithological information extraction method

The imaging spectrometer, while imaging the spatial features of the target feature, forms a narrow band with tens to hundreds of continuous spectral coverage for each spatial image element. The continuous spectral profile and diagnostic feature spectra of the feature are obtained simultaneously as the spatial image, enabling direct feature identification and quantitative information to be obtained using spectral information. Hyperspectral identification of lithology relies on the spectral characteristics of the rock, allowing the identification of rock types and the extraction of quantitative information based on measured spectra, spectral library spectra or pure image element spectra. Hyperspectral data has high spectral resolution and contains rich textural information, which facilitates lithology identification. Hyperspectral remote sensing lithology identification can be divided into three types based on individual diagnostic absorption spectral features, full spectral shape features, and spectral knowledge models.

3.2.1. Information extraction methods based on individual diagnostic absorption spectral features. Based on the individual diagnostic absorption spectral features of the end element (including the position, depth, width, area, and symmetry of the absorption), this information is extracted and enhanced from the hyperspectral data and used directly in the rockiness recognition port, e.g., HIS encoding with the absorption band map assigns brightness (H), intensity (I) and saturation (S) to the band absorption centre position image, depth image, and half-polarity width image respectively, and then transforms to RGB space for lithological mineral identification based on hue differences [12].

3.2.2. Information extraction methods based on full spectral features. The full spectral shape-based identification technique uses the entire spectral curve to evaluate the degree of similarity between the reference and image spectra in two dimensions. Spectral Matching (SM) calculates the magnitude of the difference between the image element spectrum and the reference spectrum to identify lithology; Similarity Index (SI) identifies lithology based on the mean magnitude of the sum of the squared band differences between the average spectrum of a known image element and the spectrum of an unknown image element; Spectral Angle Mapping (SAM) identifies lithology based on the magnitude of the vector angle between the image element spectrum and the reference spectrum [13]. To improve this deficiency, two mean images can be colour-synthesised with the spectral angle mapper, which reflects both the spectral shape of the lithology spectrum and the reflectance information of the lithology. Rowan et al. used HyMap hyperspectral data and applied the matching filtering method to identify ultramafic and adjacent lithologies with good results [14]. The study concluded that analysing spectral shape and reflectance in the visible NIR and short-wave IR bands is as important as analysing the characteristic spectra when lithological mapping units in weathered terrain areas.

The use of the whole spectral profile for lithology matching identification improves the effect of uncertainty in individual spectral features; the drawback is that lithology spectra are subject to variability due to various factors, as well as the unsatisfactory identification of lithologies with a little spectral variation.

*3.2.3. Information extraction methods based on spectral knowledge models. L*ithology information extraction methods based on spectral knowledge models can quantify the composition, content, and other physical characteristics of rocks while identifying lithology, which is the development direction of lithology information extraction by hyperspectral remote sensing. However, with the development of related disciplines, the recognition accuracy and quantification ability of hyperspectral lithological information extraction methods based on spectral knowledge models will be further improved.

In addition, experts have explored a series of information extraction techniques, such as hybrid spectral decomposition, MNF transformation, NAPC (Noise-adjust Principal Components Transform) transformation, principal component-based correspondence analysis, spectral angle mapping (SAM), matched filtering, and correlation band absorption [15]. In addition, this study has developed supervised, unsupervised, and decision tree classification methods for extracting remote sensing information based

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on pattern recognition, and introduced the latest achievements in artificial intelligence and data mining, such as neural network methods, wavelet transform, and expert knowledge systems.

4. Evaluation of remote sensing in lithology identification

4.1. Advantages
The advantages are a large and fast detection area and a large number of image and spectral processing tools. Data processing tools, such as data fusion, image enhancement, texture information extraction, and band ratio operations, enable accurate identification results with minimal impact from complex geographic environments.

4.2. Limitations
Many lithological classifications based on spectral information are still the same methods of remote sensing mineral extraction. The composition of minerals is single, and typical spectral morphology peaks are present in alteration minerals. The composition of rocks is complex, and there is no typical spectral information or absorption peaks, and diagnostic spectral features are missing.

The problem with classifying lithologies based on spatial information is mainly that the spatial textural characteristics of surface lithologies are complex and varied. At low spatial resolution, each lithology does not have a typical. The surface texture is highly dependent on the topographic relief. The surface texture is highly dependent on the distribution of the ground surface and is also influenced by others. The surface texture is highly dependent on topographic relief and surface distribution and is also influenced by other geological factors, resulting in a surface texture that does not truly. The results of using textural information for classification are generally poor.

Lithology classification based on multiple information composite, the method does carve field lithology information from multiple dimensions. Using multiple sources of information requires more data, a larger initial investment, and a higher upfront investment, which may be more costly.

4.3. Further development
In areas with a warm and humid climate, where the upper part of the rock is covered with thick soil and dense vegetation, the soil and vegetation information is usually represented on the image, and the lithology information is weak. The key to remote sensing lithology identification is to find ways of extracting lithological information directly without the influence of topsoil and vegetation; or key to remote sensing lithology identification is to find ways to extract lithological information directly without the influence of topsoil and vegetation, or to identify lithology by studying the association between soil, vegetation, and lithology.

Methodologically, there should be a move towards intelligence. Data processing, spectral feature extraction, sample selection, and classification methods are all influenced by a priori knowledge, staff experience, and theoretical flaws. This affects the classification accuracy to a certain extent. Current big data and artificial intelligence methods are being improved increasingly with the performance of computers, and the methods are high-speed and efficient, with strong memory capacity and no human subjective factor influence. The calculation effect has been improved to a certain extent compared with manual, and intelligent methods are being promoted in various fields. Remote sensing lithology analysis will be a direction of image processing, and intelligent recognition of remote sensing lithology will become an important technical field.

Regarding practical applications, remote sensing lithology identification methods are commonly used in geological surveys. However, many parts of the surface are covered with vegetation, and remote sensing technology does not perform well, resulting in the general application scope and effectiveness of remote sensing lithology identification. At the same time, subsurface drilling and deep drilling have become a new way for mankind to understand the earth. Applying remote sensing lithology identification methods to the field of borehole information extraction, using remote sensing spectral analysis methods to identify the lithology of cores, and fast core cataloguing are the new development direction of remote sensing lithology identification

5. Conclusion

This study uses remote sensing techniques for lithology identification in Almeria, discusses the flaws and applicability of remote sensing techniques, and proposes a combined remote sensing approach.

Lithology identification results in Almeria from remote sensing imagery synthesised using Landsat-8 multiple band sets differ from actual lithology distribution. It shows the limitations of remote sensing techniques for lithology identification. Based on the limitations of remote sensing techniques demonstrated in the case study, this paper discusses how remote sensing improves the identification and analysis of lithology in other research cases by means of technical improvements combined with other techniques. Remote sensing identification has the advantages of rapidity, wide area, and macroscopic understanding. Remote sensing is affected by atmospheric conditions, surface relief, weathering and other factors, data quality, data type, spectral resolution, and spatial resolution of the image. In practice, choosing the appropriate method according to the actual situation is necessary. Remote sensing research methods should be developed in the direction of intelligence and automation. It is suggested that the field of application of remote sensing lithology identification could be developed in the direction of geological borehole core cataloguing.

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