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Review Article

A Review of Integration Techniques of Multi-Geoscience Data-Sets in Mineral Prospectivity Mapping

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Abstract

In every sphere and utility aspects of human life, there is need of metals and construction materials. Minerals which are below the near subsurface is almost explored on the basis of direct geospatial evidences. There is high demand of metals and other materials which are mined below the surface of earth In the current landscape, there's a demand for faster and more precise exploration strategies, particularly emphasizing Greenfield exploration and deep-seated mineralization. This paper conducts a comprehensive review of existing methodologies for integrating multi-geoscience datasets aimed at mineral prognostication, with a focus on identifying the most precise and authentic Artificial Intelligence (AI) - based data integration techniques. Additionally, it offers insights into the current status of mineral exploration in India and the global evolution of data integration practices. Several types of geoscientific datasets i.e. geological, geophysical, geochemical and geospectral data have to be organized in geospatial domain for meaningful mineral exploration outcome. These datasets have been processed to extract exploratory indicator layers for data integration are called Mineral Prospectivity Mapping (MPM). Indeed, MPM is a multiple criterion decision making (MCDM) task which provide a predictive model for categorizing of sought areas in terms of ore mineralization. There after based upon Geological factors i.e. lithology, structure, shear & fault zones, alteration zones etc. of sought mineralized area, selection of drilling parameters (depth, angle, level, type, rpm, feed) is done for resource assessment. Literature survey suggests that minerals exploration by integrated approach on the basis of these datasets is still poorly performed. It has been gathered that knowledge-driven data integration using Fuzzy Gamma Operator and Multiclass Index Overlay method is best suited for mineral exploration. In past, few researchers of other countries have exploited data integration approach with encouraging results. Despite the abundance of data available in India, this approach has not been utilized very successfully and no standard protocols exist even for decision making for drilling operation. Thus, it's evident that employing the Fuzzy Inference System (FIS) algorithm, particularly utilizing the Fuzzy Gamma Operator and Multiclass Index Overlay integration method, remains underutilized in designing standardized operating procedures (SOP) for mineral exploration in India and decision-making for drilling operations. This approach holds promise for minimizing time lag and optimizing resources such as manpower, instruments, and finances.

Keywords

Mineral Exploration, Integration, Geoscience Datasets, Mineral Prospectivity Mapping, Fuzzy Inference System, Fuzzy Gamma Operator, Mineral Exploration in India, Knowledge-Driven Technique, Data–Driven Technique

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1. Introduction

In every sphere and utility aspects of human life, there is need of metals and construction materials. Nowadays, economic and sustainable development of any nation depends on the natural resources mineral wealth. Minerals which are below the near subsurface is almost explored on the basis of direct geospatial information/ evidences. So, there is high demand of metals and other materials which are mined below the surface of earth. In the present scenario, there's a demand for faster and more precise exploration strategies, particularly emphasizing Greenfield exploration, concealed / deep-seated mineralization & hydrothermal mineralization zones. To achieve the goal, multi-dimensional approach should be explored & attempted using multi-proxy data base, utilizing some other economical, precise and potential explorations techniques for sustainable development of human being, society and country.

This paper provides an in-depth examination of methodologies for integrating diverse geoscience datasets to enhance mineral prognostication accuracy, particularly emphasizing the exploration of the most reliable AI-driven integration techniques. Furthermore, it offers a succinct overview of mineral exploration in India alongside the global progression of data integration methodologies.

Majority of explorations are being done with independent exploration methods i.e., geological, geophysical, geochemical, remote sensing etc. (Figure 1). To explore/discover new minerals deposits, three main types of Geospatial datasets i.e., Geological field survey, Geophysical field survey & Geochemical lab based datasets related to specific area are being used in isolation. Majority of data sets are available with Geological survey of India (GSI), established 172 years ago. Since then, GSI is prime provider and nodal agency of basic earth science information to government, industry and general public and leader in the field of mineral exploration. Integration of above independent datasets of three surveys will allow us to model a MPM which later can be used for decision making for drilling operation and estimation of mineral resources.

Geological field survey produces datasets collected from surface of earth which is generalized as two-dimensional dataset. Rock distribution maps, fault maps, Geomorphological maps are examples of such data. Geophysical data adds one more dimension (3^{rd} dimension) to the geological dataset and provide information on the basis of physical properties of minerals & rocks, at depth derived from Gravity survey, Magnetic survey, Seismic profile, resistivity maps etc. Geochemical datasets are obtained from laboratory test conducted on sample taken from field survey using high end instruments like X- Ray Diffraction (XRD), X-Ray Fluorescence (XRF), Energy dispersive X-Ray Spectrometer (EDX), Inductively Coupled Plasma Mass Spectrometer (ICPMS) etc. for chemical analysis i.e. crystal structure, phase composition, chemical composition at surface and inside the mineral body.

Exploration geoscientists are keen to adopt new technology for the collection and processing of exploration data but are skeptical about automated interpretations of processed data. The skepticism is justified to some degree as computer software cannot match the human mind in recognizing patterns. So despite the proliferation of digital techniques, some human expertise intervention also needs to be incorporated while using computer based integration of geoscience datasets. So exploring best method to computer based integration of all type of geoscience datasets i.e. Geological, Geophysical, Geochemical, & Remote sensing data, for mineral exploration are explicitly needed & to be explored.

In context of India, this would be a Step towards '*Atmanirbhar Bharat'*. India holds promising prospects for exploration and drilling, given its wealth of unexplored minerals in significant quantities. Moreover, the future presents ample opportunities for the discovery of surface and deep-seated mineral deposits through the utilization of modern techniques like AI-based data integration methods.

One of the most significant developments in computer handling of spatial data is rise of what are now known as GIS system. GIS is a computer system both hardware and software for capture, store, manipulate, visualization and analysis of Geographically referenced data (Figure 2). GISs have been widely applied to a host of discipline such as resource assessment, municipal planning, transportation, marketing, mineral exploration, mineral resource assessment, forestry, epidemiology and many others. The common factor is simply the number of information about phenomena that are widely distributed over earth. GIS have not yet been fully exploited for mineral exploration by the Geoscientists.

In the meantime, Fuzzy logic (FL) is developed based on the fuzzy set theory proposed by Lotfi A. Zadeh of University of California at Berkeley in the year 1965. Since then, it has grown by leaps and bound. Application of fuzzy sets and fuzzy logic were ushered in by Mamdani through a paper in 1975. The development in applications were so dramatic that within 15 years both consumer products like cameras, washing machines, TV and industrial product, based on FL Controller, were rolled out in the market. FL has numerous applications in various fields- Artificial Intelligence, Automobile, computer science, expert system, medical diagnosis, neural network, robotics, social science so on. FL empowers geoscientists to apply their expertise in constructing models, which are then utilized to produce mineral potential maps and identify the key evidential layers deemed most crucial for the specific style of mineralization. The end result of these FL, GIS, IAS and other numerous data integration techniques are a series of MPMs that highlight areas of higher exploration prospectivity /prognostication for a particular commodity. These maps should accurately identify existing deposits within the study area while also indicating promising regions for the discovery of new deposits.

Different scholars utilized GIS, IAS, FIS, Multiclass Index Overlay method, other Data driven and knowledge driven methods & different publically available software which provided the capacity to integrate and combine multiple layers of geosciences datasets into mineral prospectivity maps for identification of areas for minerals exploration. Although GIS have demonstrated notable efficiency and success in MPM across various exploration domains in few countries, the integration of available various types of geoscience datasets utilizing a AI based knowledge-driven technique for mineral exploration in India remains relatively underutilized. This is immediately required for sustainable development of Railways, Telecom, Nuclear energy, Solar cell, Electric vehicle etc. commensurate with pace of development, size of economy & improvement in quality of life.

Despite India's abundant geological potential, the integrated approach to mineral exploration hasn't been extensively explored and remains underutilized in designing SOP for mineral exploration in India and decision-making for drilling operations. With increasing demand for critical minerals due to renewable energy growth and electric vehicle adoption, there's a need to tap into India's untapped mineral resources Thus, it's evident that there is an urgent need to assess the best possible data integration techniques from review of earlier research works and then to test and establish a chosen method. This approach holds promise for minimizing time lag and optimizing resources such as manpower, instruments, and finances. This will also help us in exploring concealed & deep-seated resources in economical way.

In this review paper, comprehensive examination has been made to assess the best possible integration technique for integrating abundant Geoscience datasets which could offer promising avenues for more comprehensive mineral prognostication, facilitating the development of a SOP for mineral exploration. Following the integration of geological factors such as lithology, structure, shear and fault zones, alteration zones, etc., in the sought mineralized area, developing a SOP for the selection of drilling parameters (including depth, angle, level, type, rpm, feed) could be pursued to facilitate resource assessment.

2. Status of Mineral Exploration in India

Minerals play a crucial role as essential raw materials for numerous fundamental industries and serve as a primary resource driving development initiatives. Many of these including critical minerals are essential in fulfilling the manufacturing needs of green technologies such as zero emission vehicles, wind turbine, geothermal energy exploration and exploitation, solar panels, information and communication technologies including semiconductors, superconductors and other advanced manufacturing inputs, high tech equipment, aviation and national defence. As India shifts towards renewable power generation and electric vehicles, there will be a substantial surge in the demand for numerous critical minerals [10, 55, 56].

India's demand for mineral resources is in upward trend along with population growth, advancement of urbanization and industrialization in modern context of environment & social issues. The mining industry must explore additional resources within the Earth's crust to meet the increasing demand for metals and raw materials. Mineral Exploration is inevitable early action for mineral extraction through mining sector. Mining sector is India has huge growth potential.

Conversely, the rate of discovering new ore deposits, particularly through Greenfield exploration, has steadily decreased in recent years due to challenges such as thick overburden, remote locations, declining ore grades, and social and environmental concerns. Consequently, there is a heightened expectation for technological innovations in mineral exploration to ensure the sustainability of non-renewable resources.

India possesses a distinctive geological tectonic setting that is favourable for hosting significant mineral resources. India's rich mineral wealth terms the back bone of the country and the core of its industrial economic and commercial growth. Mineral extraction in India traces its roots back to the days of the Harappa civilization. Reconnaissance and exploration of minerals must be encouraged with particular attention given to deep-seated minerals. India's mining sector so mineral exploration is still under developed as compared with other developing economics like China and Brazil. It has huge untapped potential.

India has abundant resources of minerals such as Iron, Chromite, Manganese, Bauxite, Coal, Limestone, Dolomite, Mica, Zinc, and Graphite. However, it faces shortages in resources like Nickel, Cobalt, Molybdenum, Copper, Sulphur, Potash, Apatite, Rock Phosphate, Gold, PGEs, Diamonds, and others, despite the vast potential area available in the country. In 2023, the demand for minerals is estimated to rise by 3%, driven by India's status as the third largest energy consuming nation globally and the consequent increased demand for power and electricity within the country [50].

It has been estimated that obvious geological potential (OGP) area in India contain around 1.0 Lakh Sq.km of Gold, 3.0 Lakh Sq.km of Diamond, 1.6 Lakh Sq.km of Base Metal, 8000 Sq.km of PGEs and 5000 Sq.km of iron ore. A preliminary estimate suggests that less than 2% of the total OGP area is currently mined, and less than 10% has undergone detailed exploration. Thus many greenfield areas where there could be a scope for green mineralization are yet to be explored for bulk commodities [10]. However, India has immense potential for concealed and deep-seated deposits.

The latest mineral exploration programme for minerals including critical minerals for India are not only required for achieving sustainable development & realizing the visions of "*Atma Nirbhar Bharat*". So it has become imperative to identify and develops reliable, quicker mineral exploration techniques. The use of technology in particular digital techniques based upon AI is vital to utilize available vast data to discover Brownfield and Greenfield exploration targets. This will also reduce import dependency as India is 100% import dependant on certain element like Lithium, Cobalt, Nickel, vanadium, Niobium, Germanium Rhenium, Beryllium, Strontium etc. Identifying more efficient methods for discovering the next generation of critical mineral deposits requires leveraging geological expertise, data analytics, modelling techniques, and machine learning capabilities [55, 56].

3. Evolution of Data Integration for Mineral Exploration

Integration offers numerous advantages, including enhanced potential for success and reduced exploration risk, expedited evaluation and turnover of regional data, and improved geological interpretation through comprehensive utilization of all available information. The challenge lies in implementing efficient approaches for verifying and integrating all available geoscience data in a systematic strategy to ensure increased accuracy and completeness of interpretation. In the preceding twenty years, the average cost of a new discovery has surged nearly fourfold, while the average size of deposits has decreased by 30%. The advancement of deep-sea exploration technology, coupled with the depletion of terrestrial mineral resources, has sparked significant attention from various countries. Since the first discovery of seafloor hydrothermal vents at mid-ocean ridges in the late 1970s, researchers have employed a multitude of techniques for MPM.

Numerous modeling methods for producing MPM using a GIS or IAS have been developed over past 25 years. These methods can be divided into two basic categories Knowledge-driven & Data –driven techniques. Both of these approaches are utilized to assign evidential weights and integrate various evidential maps for MCDM in drilling operations. In order to conduct MPM, multiple datasets or layers (e.g. geological, geophysical, geochemical and remote sensing data) must be collected, analyzed and integrated. The integration of different digital geoscientific data sets is a key component of MPM which has evolved over a period of three decades as a need of time.

Mineral exploration has been traditionally carried out for terrestrial resources through *"Field Survey"* by geologists, geophysicists, and geochemists primarily based on direct evidence. Nevertheless, due to the continuous and exponential increase in the demand for minerals resulting from factors such as rapid population growth, urbanization, and serious concerns over global warming, new methods are being sought.

After the introduction of computer software such as GIS and IAS in 1970, fuzzy set theory proposed by Zadeh in 1965 [80] and its application to human decision-making by Zimmermann H.J et al. [81], sparked a surge in mineral exploration activities using computer-based expert systems. These systems allowed for the integration of geoscience data into MPM to identify mineral resources. Researchers such as Bonham-Carter, G.F., Agterberg, F.P., Wright [5, 6, 18-22], Moon, W.M. et al [39, 40] and An P. [7-9], made initial successful efforts.

In last quarter of century and recent past, data mining techniques have been inspired by human intelligence, leading to a new approach to computing. Data mining involves machine-driven discoveries from data. *Machine learning algorithms (MLA)* are now widely used for mineral prospectivity modeling due to the increasing size and variety of datasets. These algorithms are efficient and can handle large, high-dimensional datasets with non-Gaussian distributions [15]. The models generated are robust and can be used to identify exploration targets. Classical prospectivity modeling has been dominated by Weights-of-Evidences (WoE) and Fuzzy logic (FL) methods. While MLA is more data-driven and effective than WoE, they do require a large and diverse training dataset. The FL technique is knowledge-based and founded on fuzzy set theory, allowing users to incorporate their knowledge into the model through various data transformations. The work by Nykanen et al [59-61] and Burkin et al [26] incorporated the evidence layers' concept, allowing multiple evidence layers to be produced from data and enhancing the fuzzy transformation and FIS.

An important method of data mining is provided by *"Visualization or 2D imaging"***.** Human brain has great capacity to decipher and make sense of complicated data if the information is presented clearly in the form of Map, to the eye. During last three decades, significant progress has been made in ways of displaying information visually for best possible interpretation. The introduction of color imaging as 2D imaging was one of those strides. So subtle features can be emphasized or picked out in an individual data set. Next step was to bring multidisciplinary data together in a so called GIS, which allowed people to integrate 2D datasets either by laying them out and tracking them side by side or by overlapping them at the same scale. GIS programs like ArcView, MapInfo, and ArcGIS offer the capability to manage and query databases, empowering users to extract valuable insights from large datasets and make informed decisions based on spatial analysis results [15].

Inversion of geophysical data from basic field measurements to interpreted physical rock properties using 3 dimensionally software brought *"3D interpretation/visualization*". Over the past two decades, various technologies have converged to create advanced 3D visualization software like "Gocad". The term common earth model (CEM) has been coined to describe geologic model that have been built by integration of cross-disciplinary datasets (Garret et al [44]; McGaughey et al. [54]). The diverse range of data in mineral exploration poses additional challenges for intuitive interpretation of 3D visualization based upon fusion of multiple datasets.

Multilayer exploration datasets, however, they typically contain intricate numerical correlations that visualization alone may not uncover. It is important, then, to supplement visualization with *"Statistical Data Mining & pattern recognition techniques i.e. Probabilistic Modelling"*. In an exploration case, the most useful product of a statistical analysis is an estimate of the conditional probability that a deposit occurs at some location. Following methods such as WoE (widely used for MPM earlier by Bonham-Carter [21], Raines [68], Kemp et al [49], Functional approximation / Neural Network (Poulton et al [67], Brown et al [24, 25], Bougrain et al [23] and Radial basis function (Singer and Kouda [72, 73]; Harris and Pan [45]; Harris et al [46, 47]; Porwal et al [63-65]. Various *"Non-Probabilistic methods"* also have been tried successfully for computer based prospectivity modelling using Boolean fuzzy logic methods /systems [15]. In the past three decades, the use of MLA for MPM has been driven by the increasing size of individual datasets and range of data type available for mineral exploration.

Several approaches to MPM are categorized into Data-Driven and Knowledge-Driven methods (Bonham-Carter [21], Carranza [34-36], Harris and Pan [45]). In Data-Driven or empirical techniques, the known mineral deposits in a region of interest are used as 'Training points' to established spatial relationship between the known deposits and particular geological, geophysical and geochemical features. The connection between evidential maps and the tailing points is quantified, determining the significance of each evidence map (Carranza and Hale [32, 33]), and subsequently integrated into a unified MPP (Nykanen and Salmirinne [59]). Example of empirical methods of MPM are weight of evidence (Bonham-Carter et al [19]; Carranza and Hale [31]), Logistic Regression (Agterberg and Bonham-Carter [22]; Carranza and Hale [28]), neural networks (Porwal et al [63, 64]; Singer and Kauda [72]), evidential belief functions (Carranza [32, 34]), Bayesian network classifiers (Porwal et al [65] and support vector machines (Abedi et al [2]; Zuo and Carranza [83]). The Knowledge-Driven methods [53] are those where mineral deposits are predicted with the help of expert experience & judgement. This include use of Boolean logic (Bonham-Carter [18]), index overlay (Bonham-Carter [19], Carranza [27], Sadegahi et al [71], the Demster-Shafer belief theory (Moon [58]), fuzzy logic overlay & inference system (An et al [7], Chung and Moon [39], Porwal A. et al [66], Barak et al [11-14], Sun et al [75]), wildcat mapping (Carranza [37, 38], Carranza and Hale [29]) and outranking methods (Abedi et al [4]). Data-driven modeling methods typically operate within areas with known occurrences, while knowledge-driven techniques are better suited for "Greenfields Exploration" regions.

FIS, one of the methods of Knowledge-driven techniques to integrate the exploration layers including geological, geophysical, geochemical and remote sensing data. FIS is a mapping technique in which the FL applies the inputs to provide outputs as described in figure 3. FIS can illustrate an exploration geoscientist's reasoning in predicting mineral potential by integrating predictor linguistic variables. These techniques require experience & expertise of a geoscientist to define fuzzy scores to prepare probability maps which later used for drilling boreholes location determination for drilling operations.

In India also, there is urgent need for such integrated approach for minerals resources exploration.

4. Historical Background

Mineral exploration endeavors to uncover new mineral deposits within a designated region. A primary objective of this process involves identifying prospective areas within the region of interest. Diverse geo-datasets, including geological, geophysical, and geochemical data, are gathered, analyzed, and merged for MPM to delineate prospective areas. Thus MPM is a MCDM task and produces a predictive model for outlining prospective areas.

In recent major research work where such approach were used i.e. Venkataraman et al [77] attempted limited data integration through using Baysian statistics based on WoE method and fuzzy logic algorithm for base metal in Rajasthan area, India, Tangestani and Moore [76] applied data integrated approach using three principal component analysis (PCA) on alteration mapping based on Landsat TM bands in Iran, Lunden and Wang [52] attempted integration of remote sensing data with geophysical data etc. in a GSI platform for exact geological interpretation only, Wolfgang [78] attempted geophysical datasets i.e. geomagnetic and geo-electrical data using GIS for archaeological investigation only. R. Derakhshani et al [41] used fuzzy logic model for geological data only for Porphyry Copper MPM in area of Iran. G. F. Bonham-Carter et al [18] applied Bayes rule based integration of geological, airborne geophysical and geochemical survey data using GIS quadtree structure for Gold MPM in Nova Scotia, Canada. M. Abedi et al [1] attempted ELECTRE III, MCDM technique (outranking approach of operations research) by integration of geological, geophysical and geochemical datasets for Copper MPM in Kerman, Iran. Yue Liu et al [51] applied data-driven WoE and fuzzy logic models for comparative study from multisource geospatial datasets i.e. geological, geophysical and geochemical for Tungsten MPM for South China. Alok Porwal et al [66] discussed Fuzzy inference system (knowledge driven artificial intelligence system) as a case study to create MPM of Uranium in Western Australia. S.Barak et al [11-14] explored Copper using Fuzzy inference system based data integration technique for multi geoscience datasets in Iran. Satyabrata Behera et al [16] attempted hybrid model utilizing WoE and FL (WOE-FL) to create a MPM on GIS platform for known resources of Gold in Hutti belt India. H. Sabbaghi et al [70] applied TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) which is knowledge driven technique for Copper-Molybdenum in Iran.

The summary of salient research work in the related field is being provided in chronological order.

G. F. Bonham-Carter [18] utilized a variety of regional geoscience datasets from Nova Scotia, Canada and analyzed using GIS. The datasets include bedrock and surficial geological maps, airborne geophysical survey data, geochemistry from lake sediment samples, and mineral occurrence data. A gold occurrence map based solely on geochemistry was generated. Additionally, Bayes's rule-based integration of geological, airborne geophysical and geochemical survey data using GIS was employed to incorporate other factors.

P. An et al [62] used Fuzzy set theory using algebraic sum and Gamma operator (Knowledge-Driven approach) was applied for investigation and testing with mine datasets of geology & geophysical from Farley lake area, Canada. Possibility distribution maps were derived which have successfully outlined favorable area for base metal deposit and iron formation deposits.

Brown et al [24] studied on multilayer feed –forward neural network (Data-Driven approach), trained with a gradient decent, back-propagation algorithm, used to estimate the favorability for gold deposits using a raster GIS database in New South wales. The database consists of geology, regional faults, airborne magnetic and gamma ray survey data and 63 deposit and occurrence locations. The result of this study offered several advantages over existing methods.

Venkataraman et al [77] attempted to integrate different da sets such as Landsat TM, airborne magnetic, geochemical, geological and ground-based data of Rajpura-Dariba Rajasthan India through GIS using hybrid integration of Data-Driven approach and Knowledge-Driven approach. They used (I) Bayesian statistics based on the weights of evidence method and (2) a fuzzy logic algorithm to derive spatial models to target potential base metal mineralized areas for future exploration. The final produced map indicated four categories of potential zones for sulfide mineralization on the basis of posterior probability & fuzzy set approval (using Bayesian statistics).

Tangestani and Moore [76] compiled, evaluated, and integrated diverse spatial geological data to create a potential map for porphyry copper deposits in northern Shahr-e-Babak, Iran. Technique used was Principal Component Analysis (PCA) i.e. Crosta technique, a type of Data-Driven approach. Aeromagnetic data were also used to extract magnetic anomalies and extra liniments. The final map highlighted the most important known copper deposits in high favorability domains.

Maysam Abedi et al [1] explored the application of the MCDM technique known as ELECTRE III, a type of Knowledge-Driven method commonly used in operations research, to MPM. They combined evidential map layers obtained from geological, geophysical, and geochemical datasets. In a case study, thirteen evidential map layers were utilized for MPM in the region encompassing the Now Chun copper prospect in Iran's Kerman province. The outputs were validated using 3D models of copper and molybdenum concentrations from 21 drill hole areas. This approach demonstrated excellent performance in MPM.

Maysam Abedi et al [3] used Bayesian and neural techniques, a type of Data-driven approach, to generate a prospectivity map for porphyry –Cu deposits. Various layers of geological, geophysical, and geochemical data were integrated to assess the Now Chun porphyry-copper deposits in Iran's Kerman province and to generate a prospectivity map for mineral exploration. Both methods showed correct classification rates of 52.38% and 80.95% for 21 boreholes.

Yue Liu et al [52] employed Data-driven WofE and Knowledge-Driven Fuzzy Logic models to assess tungsten polymetallic deposits in the Nanling metallogenic belt, South China. Initially, seven ore-controlling factors sourced from various geospatial datasets (geological, geochemical, and geophysical) were utilized for data integration in both models. Two MPM were created, efficiently pinpointing the deposit locations. The WofE map accurately predicted 81% of the deposits within 13.6% of the study area, while the fuzzy logic map forecasted 81.5% of the deposits within 13% of the area. Overall, both models demonstrated satisfactory capabilities in accurately identifying regions containing known mineral deposits.

Alok Porwal et al [66] described Mamdani-type fuzzy inference system i.e. Knowledge-Driven method, for prospectivity modelling of mineral system and then case study for surficial uranium prospectivity modelling in the Yeelirrie area, Western Australia was performed. In the output prospectivity map, some area showed high probability.

J. R. Harris et al [48] used Data-driven (used Random forest (RF) supervised classifier technique) and Knowledge-driven (used weighted –index overlay method) techniques to produce regional Gold prospectivity maps of a portion of Melville Peninsula, Northern Canada using geophysical and geochemical data. RF technique outperformed the weighted-index overlay while predicting of the known Gold occurrence.

Nannan Zhang et al [82] used weights-of-evidence model (Data-Driven method) and fuzzy logic model (Knowledge-driven method) for MPM. Geological maps, geochemical samples and data from known gold deposits of Western Junggar area, Xinjiang Province, China and then integrated using expert knowledge for probable mineral occurrences. The MPM using fuzzy logic methods demonstrated validity. In areas with numerous deposits, data-driven approaches for MPM were deemed suitable. However, in cases where sufficient data are lacking, knowledge-driven approaches, such as the fuzzy logic method utilized in this study, often yield superior results.

S. Barak et al [11] used Knowledge driven FIS to integrate the exploration layers including geological, remote sensing, geochemical and magnetic data for porphyry copper deposit of the Kahang area, Iran. MPM was obtained and compared with the 33 drilled boreholes in the studied area. 70.6% accuracy between model result and true data from the boreholes were achieved and consequently the appropriate areas were suggested for the subsequent drilling.

S. Barak et al. [12] employed a Knowledge-driven FIS to integrate copper exploration layers in Neysian, Iran. The output of the FIS was a classified mineral potential map, which exhibited a 70.6% agreement with the 33 drilled boreholes.

S. Barak et al. [13] utilized a Knowledge-driven FIS to generate a copper MPM in the Saveh area of Iran's Markazi province. They incorporated seven indicator layers extracted from geological, geochemical, and geophysical datasets into a geospatial database for data integration. A fuzzy gamma operator is applied during the initial phase of exploratory data integration to generate three criterion layers from geology, geophysics, and geochemistry, respectively. In the second phase, FIS was implemented in three steps. Subsequently, in the third phase, MPM was conducted. To assess the accuracy of the FIS method, data from 18 boreholes were utilized. Ultimately, copper mineralization was identified, and the eastern and central portions of the Saveh prospect were identified as favorable potential zones for further mining operations.

Christopher M. Yeomans et al [79] utilized a hybrid integration approach, combining knowledge-driven feature extraction with a data-driven machine learning approach, for tungsten mineralization. They employed the data-driven Random Forest algorithm to model tungsten mineralization in Southwest England, utilizing various geological, geochemical, and geophysical evidence layers. Fuzzy set theory was also used as a part of an augmented feature extraction step. The use of fuzzy data transformation mean feature extraction added some user-knowledge about mineralization. Legacy mining data from drilling reports and mine descriptions were employed for additional validation of the fuzzy-transformed models. In essence, the modeling workflow presented a unique fusion of knowledge-driven feature extraction and data-driven machine learning modeling.

P. K. Singh et al [74] used knowledge driven approach i.e index overlay with multi class and Fuzzy logic modelling to integrate geological, geochemical, geophysical and remote sensing datasets for gold prognostication for area mainly falling in Sonbhadra district, southern part of Uttar Pradesh. This integration was done using subjective weightage for evidence maps and class score. The result of modelling was validated with known occurrences of gold mineralization.

Samaneh Barak et al. [14] assessed the effectiveness of different fuzzy-based fusion methods in MPM. They utilized these methods to address a MCDM problem aimed at designing a layout for drilling supplementary boreholes through a thorough analysis of geospatial datasets. Knowledge driven methods like fuzzy gamma operator, FIS, fuzzy outranking, fuzzy c-mean clustering and fuzzy ordered weighted averaging (FOWA) were used. Kahang porphyry Cu-Mo deposit in Iran was chosen as a case study to examine the performance of these fuzzy methods in MPM. It was found that FIS and FOWA had the highest efficiency with 80% & 78% respectively.

Satyabrata Behera et al [16] employed Data-driven (WoE), Knowledge-driven (FL), and a hybrid model integrating WoE and FL. Their aim was to map gold prospectivity and derive optimal exploration targets in a section of the Hutti-Maski schist greenbelt in India, covering 1352 square km and containing 20 known gold occurrences. They created 16 spatial evidential raster layers on a GIS platform, incorporating predictive indicators crucial for gold exploration. Various geological data sources, geochemical anomalies, and hypothermal alteration zones obtained from digital image processing of Landsat and satellite imagery were combined to produce MPM aimed at delineating future targets. Comparative analysis revealed that the hybrid model, specifically the WoE-FL model, exhibited the highest efficiency, achieving a predictive rate of 87%. Additionally, low-risk exploration targets were identified based on uncertainty assessment.

Fanous Mohammadi et al [57] in his research article aimed to assess and compare GIS-based Knowledge-driven fuzzy models for generating an orogenic gold prospectivity map in the Saqqez area, located in northwest Iran. Five fuzzy operators, including AND, OR, FAP, FAS, and GAMMA, were employed on the predictor maps to identify the most effective prediction model. However, maps generated by the AND, OR, FAP, and FAS operators proved to be inaccurate and failed to precisely identify the locations of discovered gold occurrences. In contrast, the GAMMA operator yielded acceptable results, accurately identifying potentially economic target sites. Its effectiveness in predicting and defining cost-effective target sites for orogenic gold deposits, as well as optimizing mineral deposit exploitation, was demonstrated.

Hamid Sabbaghi et al. [70] investigated the efficacy of the well-known MCDM technique, i.e. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), for improved and precise evaluation of porphyry copper-molybdenum deposits in the central region of the Urumieh-Dokhtar volcanic arc in Iran. Typically, various evidence layers consist of raster maps, including geological, geochemical, and geophysical data, which are integrated to generate a MPM. TOPSIS relies on comparing all the alternatives involved in the problem. TOPSIS can provide a more precise investigation of a region of interest compared to other knowledge-driven integration methods. The final detailed map was generated using the TOPSIS technique, and its outputs were validated through comparison with field reconnaissance and data from 24 boreholes. This method helps prevent unnecessary additional drilling in a study area.

Benjamin B et al [17] examined multi-index overlay and fuzzy logic models, both representing Knowledge-driven approaches, for mapping lode-gold prospectivity in the Ahafo gold district of southwestern Ghana using GIS. To identify potential zones for lode-gold mineralization in the study area, weighted evidential layers were merged to produce multi-index overlay and fuzzy prospectivity maps. The discretized multi-index overlay prospectivity map accurately predicted 76% of known occurrences, covering 24% of the study area as prospective. Meanwhile, the discretized fuzzy prospectivity map predicted 74% of known occurrences, encompassing 26% of the study area.

Masoud esmailzadeh et al [43] used Knowledge driven methods to combine the geological, remote sensing and geochemical data in order to generate MPM in the Kighal-Bourmolk Cu-Mo porphyry deposits in Iran. By examination of the created layers, the consistency of the potential areas was verified by field surveys. Subsequently, weights were assigned to each layer, considering the conceptual model of the porphyry copper system. Following this, the layers were integrated using the fuzzy gamma operator technique, resulting in the generation of the final MPM. Regarding the generated MPM, 0.86% of the studied areas shows a high potential mineralization and these areas were proposed for the subsequent exploration drilling locations.

5. Discussion

The ultimate goal of a mineral exploration project is to detect new economical deposits in a region of interest. Collecting simultaneously various geospatial datasets e.g. geology, geophysics and geochemistry, processing these data to extract exploratory indicator layers and data integration are called MPM.

Considering today word of digitization and availability of data analytics tools along with the vast geo scientific manpower expertise, acumen & information available with such a prestigious GSI, it is immediate need to strengthen further the mineral exploration techniques for Greenfields exploration based resources in optimal ways in our country also. Majority of datasets are available with Geological survey of India. These datasets are collected independently by Geological, Geophysical, Geochemical, national aero-geophysical mapping (NAGPM), Drilling extensive field over a period of last 172 years.

Exploration data sets are either categorical (e.g. geology) or ratio (geophysics, geochemistry). The latter is easily incorporated in a FIS whereas former cannot be directly input to Fuzzy membership functions to calculate their fuzzy membership values. There are two possible methods to handle categorical data; first, get an expert-based ranking which converts them into ordinal data and then input the latter into appropriate fuzzy membership functions.

Earlier researcher utilized GIS, IAS, FIS, Multiclass Index Overlay method, other Data driven and knowledge driven methods to integrate and combine multiple layers of geosciences datasets into mineral prospectivity maps for identification of areas for minerals exploration. The integration of FIS and multiclass index overlay methods with GIS platforms for mineral exploration in India remains relatively underutilized. Therefore, integrated dataset approaches need to be tried more exhaustively for mineral exploration in order to minimize time lag & optimization of resources i.e. man, instruments and money and to validate the technique with drilling boreholes data.

FIS utilizing the platform of GIS is well known MCDM methods. FIS is a widely accepted MCDM technique due to its sound logic, simultaneous consideration of ideals & non ideal solutions and easily programmable computation procedure. FIS which is a type of Knowledge-driven technique with AI system, is transparent, easy to build and interpretable by experts in this field as built in natural language.

Integration of datasets of three surveys will allow us to model a MPM which later can be used for decision making for drilling operation and estimation of mineral resources. The seamless integration and interoperability of exploration data play pivotal roles in mineral exploration. They empower us to amalgamate, analyze, and visualize diverse data types and sources, fostering the generation of novel insights and mitigating uncertainty to facilitate credible predictions. So, well-established FIS algorithm can be more explored for the mineral potential modelling especially observing the effectiveness of fuzzy Gamma operator in the field of “Greenfield Exploration”.

Therefore, it has been established that there is an immediate need for more precise AI based data integration technique as large volume of data in digital and Map form is available. In contemporary integrated exploration practices, a key objective is to incorporate mathematically sound representations of information derived from various datasets. This involves developing effective tools capable of accurately and efficiently combining evidence from each dataset to derive the most reasonable and realistic interpretations. For this purpose, FIS provides a more precise method of representing the information contend of different dataset and of combining them with a choice of processing operation.

6. Conclusion & Research gap

Literature survey suggests that minerals exploration by integrated approach on the basis of these datasets is still poorly performed. It has been gathered that knowledge-driven data integration using Fuzzy Gamma Operator and Multiclass Index Overlay method is best suited for mineral exploration. Multiclass Index Overlay model & fuzzy Gamma Operator [42, 43, 69] have more flexibility and ability for prognostication.

In past, few researchers of other countries have exploited data integration approach with encouraging results. Thus, it's evident that despite the abundance of data available in India, employing the FIS algorithm, particularly utilizing the Fuzzy Gamma Operator and Multiclass Index Overlay integration method, remains underutilized. Hence such techniques should be tried in future research for mineral exploration particularly in context of India. This will also assist designing SOP for mineral exploration in India and decision-making for drilling operations. This approach holds promise for minimizing time lag and optimizing resources such as manpower, instruments, and finances. This will also help us in exploring concealed & deep-seated resources in economical way.

Future research could extensively utilize FIS in a three-phase synthesis to create MPM. Initially, a Fuzzy gamma operator would amalgamate primary criteria such as geology, geophysics, geochemistry, and remote sensing data. Subsequently, FIS would integrate these criteria into a unified MPM with input from geoscientific experts. Finally, a multifractal approach would classify the map into favorability zones, guiding exploratory drilling for resource assessment, crucial for subsequent mining endeavors.

Despite India's abundant geological potential, the integrated approach to mineral exploration hasn't been extensively explored. With increasing demand for critical minerals due to renewable energy growth and electric vehicle adoption, there's a need to tap into India's untapped mineral resources. Evaluating fuzzy-based fusion functions like the Fuzzy Gamma operator for MPM development is crucial for designing a SOP for mineral exploration and drilling operations. This evaluation should involve comprehensive testing and analysis using weighted aggregates of evidence and multiclass index overlay methods applied to geospatial datasets, tailored to India's unique context.

In the context of India, it is found that exploring the application of techniques such as Multiclass Index Overlay method and Fuzzy Gamma Operator on FIS for integrating abundant Geoscience datasets could offer promising avenues for more comprehensive mineral prognostication, facilitating the development of a SOP for mineral exploration. Following the integration of geological factors such as lithology, structure, shear and fault zones, alteration zones, etc., in the sought mineralized area, developing a SOP for the selection of drilling parameters (including depth, angle, level, type, rpm, feed) could be pursued to facilitate resource assessment.

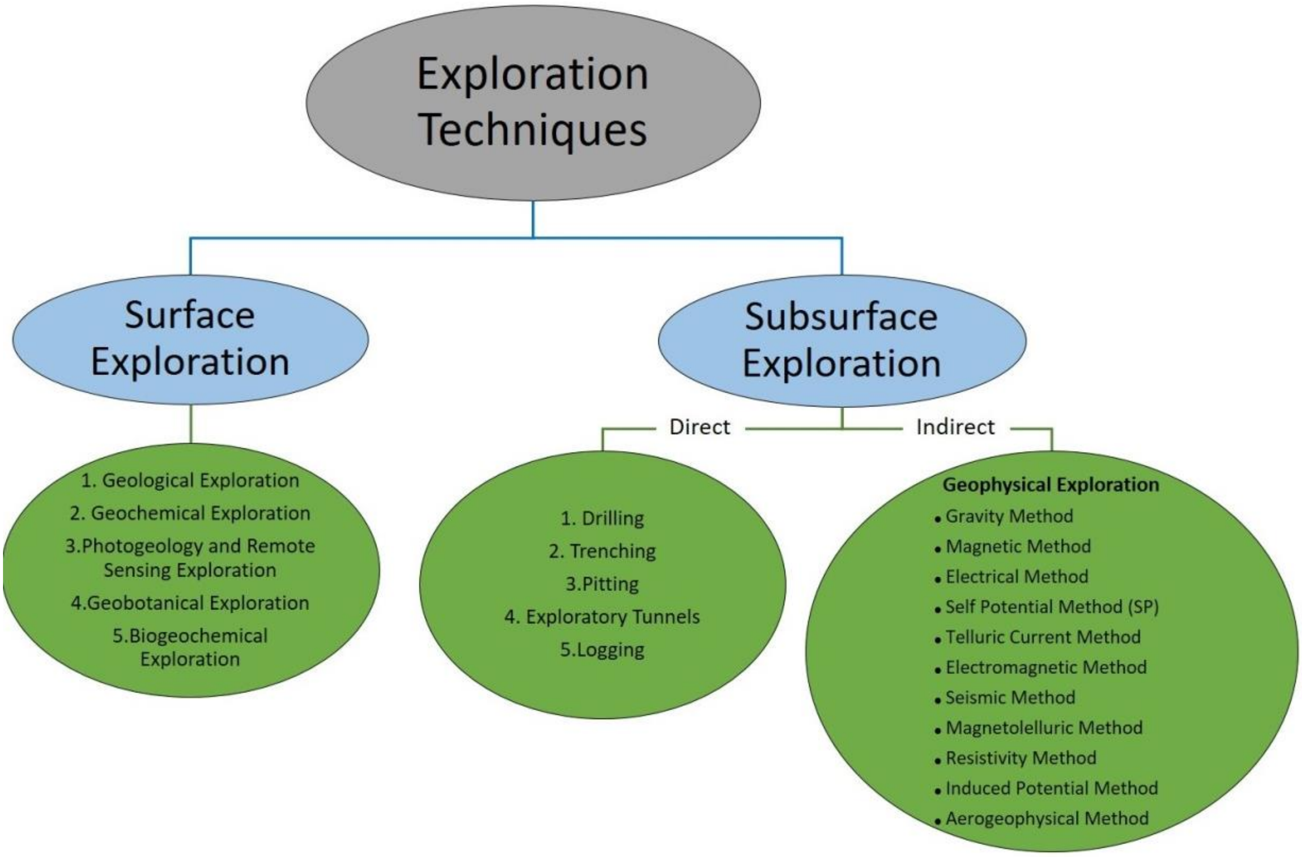

Figure 1. *Types of Exploration methods.*

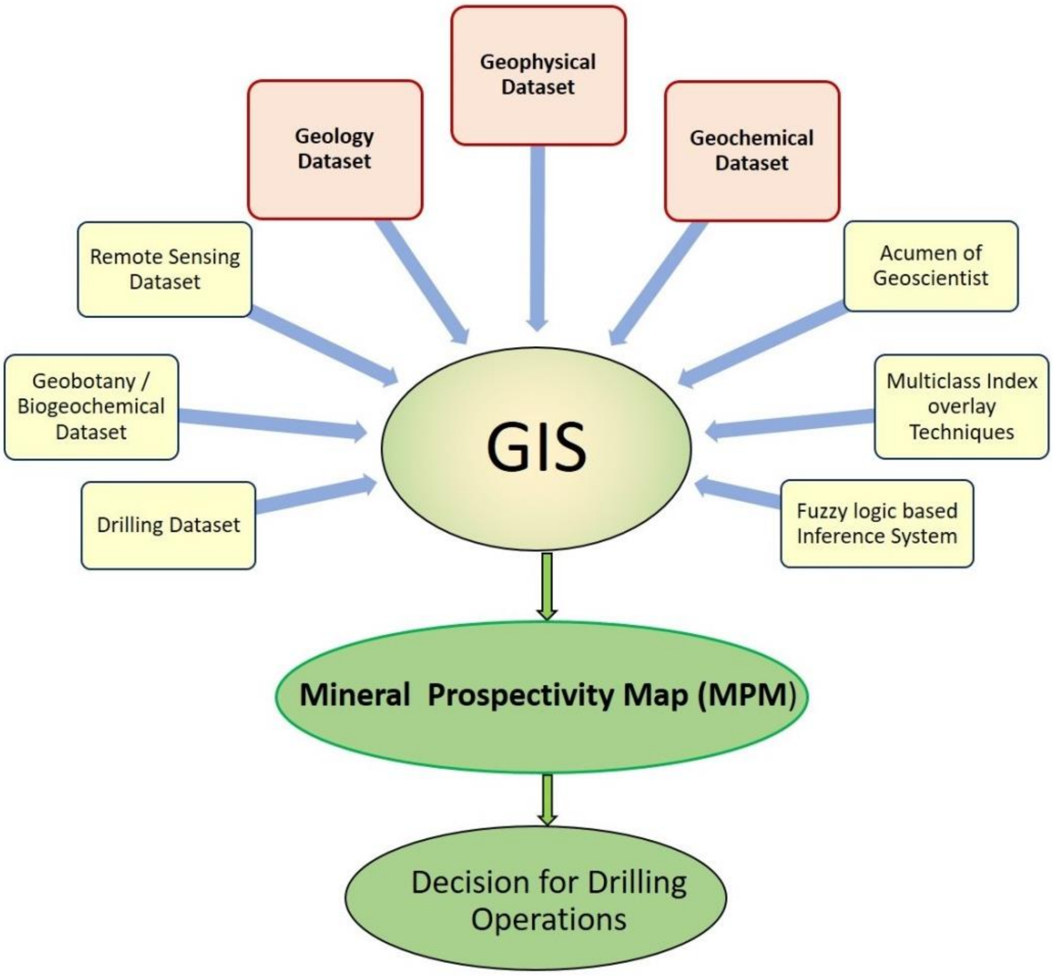

Figure 2. Geological Information System (GIS).

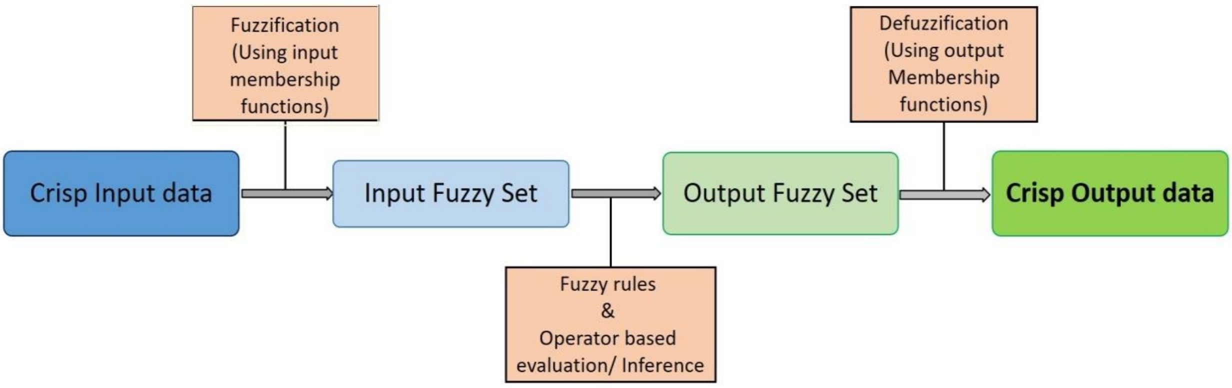

Figure 3. Working of Fuzzy Inference System (FIS).

Author Contributions

Neelesh Katiyar: Conceptualization, Data Curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Visualization, Validation, Writing-Original draft, Writing- review & editing

Asita Kulshreshta: Conceptualization, Methodology, Supervision, Writing review & editing

Pramod Kumar Singh: Conceptualization, Supervision, Validation, Writing review & editing

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Abedi, M., Torabi, S. A., Norouzi, G. H., & Hamzeh, M. (2012). ELECTRE III: A knowledge-driven method for integration of geophysical data with geological and geochemical data in mineral prospectivity mapping: Journal of applied geophysics, v87, pp9-18. https://doi.org/10.1016/j.jappgeo.2012.08.003

[2] Abedi, M., Norouzi, G. H., & Bahroudi, A. (2012). Support vector machine for multi-classification of mineral prospectivity areas: Computers & Geosciences, v46, pp272-283. https://doi.org/10.1016/j.cageo.2011.12.014

[3] Abedi, M., & Norouzi, G. H. (2012). Integration of various geophysical data with geological and geochemical data to determine additional drilling for copper exploration: Journal of Applied Geophysics, v83, pp35-45. https://doi.org/10.1016/j.jappgeo.2012.05.003

[4] Abedi, M., Norouzi, G. H., & Fathianpour, N. (2013). Fuzzy outranking approach: a knowledge-driven method for mineral prospectivity mapping. International Journal of Applied Earth Observation and Geoinformation, 21, 556-567. https://doi.org/10.1016/j.jag.2012.07.012

[5] Agterberg, F. P. (1989). Systematic approach to dealing with uncertainty of geoscience information in mineral exploration: In Proceedings of the 21st APCOM Symposium, Las Vegas, USA, 1989, pp. 165-178.

[6] Agterberg, F. P., Bonham-Carter, G. F., & Wright, D. F. (1990). Statistical pattern integration for mineral exploration. In Computer applications in resource estimation, pp. 1-21. Pergamon. https://doi.org/10.1016/B978-0-08-037245-7.50006-8

[7] An, P., Moon, W. M., & Rencz, A. (1991). Application of fuzzy set theory for integration of geological, geophysical and remote sensing data: Canadian Journal of Exploration Geophysics, v27(1), pp1-11.

[8] An, P., Moon, W. M., & Bonham-Carter, G. F. (1992). On knowledge-based approach of integrating remote sensing, geophysical and geological information: In [Proceedings] IGARSS'92 International Geoscience and Remote Sensing Symposium, v 1, pp 34-38, IEEE. https://doi.org/10.1109/IGARSS.1992.576620

[9] An, P., Moon, W. M., & Bonham-Carter, G. F. (1994). An object-oriented knowledge representation structure for exploration data integration: Nonrenewable Resources, v3, pp132-145.

[10] Assocham report (2022): Indian Mineral & Mining Sector-Steps towards Atma nirbhar Bharat. Available from: www.assocham.org.

[11] Barak, S., Bahroudi, A., & Jozanikohan, G. (2018). Exploration of Kahang porphyry copper deposit using advanced integration of geological, remote sensing, geochemical, and magnetics data: Journal of Mining and Environment, v9(1), pp19-39. https://doi.org/10.22044/jme.2017.5419.1357

[12] Barak, S., Bahroudi, A., & Jozanikohan, G. (2018). The use of fuzzy inference system in the integration of copper exploration layers in Neysian: Journal of Mining Engineering, v13(38), pp97-112. https://doi.org/10.22034/ijme.2018.30564

[13] Barak, S., Abedi, M., & Bahroudi, A. (2020). A knowledge-guided fuzzy inference approach for integrating geophysics, geochemistry, and geology data in a deposit-scale porphyry copper targeting, Saveh, Iran: Bollettino di Geofisica Teorica ed Applicata, 61(2). https://doi.org/10.4430/bgta0302

[14] Barak, S., Imamalipour, A., Abedi, M., Bahroudi, A., & Khalifani, F. M. (2021). Comprehensive modeling of mineral potential mapping by integration of multiset geosciences data: Geochemistry, v81(4), pp125824. https://doi.org/10.1016/j.chemer.2021.125824

[15] Barnett, C. T., & Williams, P. M. (2005). Mineral exploration using modern data mining techniques (Book chapter), Special publication of the Society of economic geologists, v12, pp295-310. https://doi.org/10.5382/SP.12.15

[16] Behera, S., & Panigrahi, M. K. (2022). Gold prospectivity mapping and exploration targeting in Hutti-Maski schist belt, India: Synergistic application of Weights-of-Evidence (WOE), Fuzzy Logic (FL) and hybrid (WOE-FL) models: Journal of Geochemical Exploration, 235, 106963. https://doi.org/10.1016/j.gexplo.2022.106963

[17] Boadi, B., Raju, P. S., & Wemegah, D. D. (2022). Analysing multi-index overlay and fuzzy logic models for lode-gold prospectivity mapping in the Ahafo gold district–Southwestern Ghana: Ore Geology Reviews, 148, 105059. https://doi.org/10.1016/j.oregeorev.2022.105059

[18] Bonham-Carter, G. F., Agterberg, F. P., & Wright, D. F. (1989). Integration of geological datasets for gold exploration in Nova Scotia: Digital geologic and geographic information systems, v10, pp15-23. https://doi.org/10.1029/SC010p0015

[19] Bonham-Carter, G. F. (1989). Integrating Geological Datasets with a Raster-Based Geographic Information System: Digital Geologic and Geographic Information Systems (a book), v10, pp1-13.

[20] Bonham-Carter, G. F., & Agterberg, F. P. (1990). Application of a microcomputer-based geographic information system to mineral-potential mapping: In Microcomputer applications in Geology v2, pp. 49-74, Pergamon. https://doi.org/10.1016/B978-0-08-040261-1.50012-X

[21] Bonham-Carter, G. F. (1994). Geographic information systems for geoscientists-modeling with GIS: Computer methods in the geoscientists, v 13, p398.

[22] Bonham-Carter, G. F., & Agterberg, F. P. (1999). Arc-WofE: a GIS tool for statistical integration of mineral exploration datasets. Bull Int Stat Inst, 52, 497-500.

[23] Bougrain, L., Gonzalez, M., Bouchot, V., Cassard, D., Lips, A. L., Alexandre, F., & Stein, G. (2003). Knowledge recovery for continental-scale mineral exploration by neural networks. Natural Resources Research, 12, 173-181. https://doi.org/10.1023/A:1025123920475

[24] Brown, W.M., Gedeon, T.D., Groves, D.I. and Barnes, R.G., (2000). Artificial neural networks: a new method for mineral prospectivity mapping: Australian journal of earth sciences, v47(4), pp. 757-770. https://doi.org/10.1046/j.1440-0952.2000.00807.x

[25] Brown, W., Groves, D., & Gedeon, T. (2003). Use of fuzzy membership input layers to combine subjective geological knowledge and empirical data in a neural network method for mineral-potential mapping: Natural Resources Research, v12, pp183-200. https://doi.org/10.1023/A:1025175904545

[26] Burkin, J. N., Lindsay, M. D., Occhipinti, S. A., & Holden, E. J. (2019). Incorporating conceptual and interpretation uncertainty to mineral prospectivity modelling. Geoscience Frontiers, 10(4),1383-1396. https://doi.org/10.1016/j.gsf.2019.01.009

[27] Carranza, E. J. M., Mangaoang, J. C., & Hale, M. (1999). Application of mineral exploration models and GIS to generate mineral potential maps as input for optimum land-use planning in the Philippines: Natural Resources Research, v8(2), pp165-173. https://doi.org/10.1023/A:1021846820568

[28] Carranza, E. J. M., & Hale, M. (2001). Logistic regression for geologically constrained mapping of gold potential, Baguio district, Philippines. Exploration and Mining Geology, 10(3), 165-175. https://doi.org/10.2113/0100165

[29] Carranza, E. J. M., & Hale, M. (2002). Wildcat mapping of gold potential, Baguio district, Philippines. Applied Earth Science, 111(2), 100-105. https://doi.org/10.1179/aes.2002.111.2.100

[30] Carranza, E.J.M. (2002). Geologically-constrained Mineral Potential Mapping (Examples from Phillippines): ITC Publication No. 86, International Institute for Aerospace survey and Earth Sciences(ITC), The Netherlands.

[31] Carranza, E. J. M., & Hale, M. (2002). Where are porphyry copper deposits spatially localized? A case study in Benguet province, Philippines: Natural Resources Research, v11, pp45-59. https://doi.org/10.1023/A:1014287720379

[32] Carranza, E. J. M., & Hale, M. (2002). Weights of Evidence Modeling with Small Number of Deposits to Map Mineral Prospectivity, Abra area, Philippines. Deposits and Geoenvironmental Models For Resources Exploitation and Environmental Security II, 59.

[33] Carranza, E. J. M., Woldai, T., & Chikambwe, E. M. (2005). Application of data-driven evidential belief functions to prospectivity mapping for aquamarine-bearing pegmatites, Lundazi district, Zambia: Natural Resources Research, v14, pp 47-63. https://doi.org/10.1007/s11053-005-4678-9

[34] Carranza, E. J. M., Hale, M., & Faassen, C. (2008). Selection of coherent deposit-type locations and their application in data-driven mineral prospectivity mapping: Ore geology reviews, v33(3-4), pp536-558. https://doi.org/10.1016/j.oregeorev.2007.07.001

[35] Carranza, E. J. M., & Hale, M. (2009). Handbook of exploration and environmental geochemistry. Chapter, 7, Knowledge-driven modelling of mineral prospectivity, v11, pp 189-247.

[36] Carranza E. J. M. (2009). Handbook of Exploration and Environment Geochemistry, Chapter 8: Data-Driven Modeling of Mineral Prospectivity, v11, pp 249-310.

[37] Carranza, E. J. M. (2010). Mapping of anomalies in continuous and discrete fields of stream sediment geochemical landscapes: Geochemistry, v10(2), pp171. https://doi.org/10.1144/1467-7873/09-223

[38] Carranza, E. J. M. (2010). Improved wildcat modelling of mineral prospectivity. Resource geology, 60(2), 129-149. https://doi.org/10.1111/j.1751-3928.2010.00121.x

[39] Chung, C. J. F., & Moon, W. M. (1991). Combination rules of spatial geoscience data for mineral exploration: Geoinformatics, v2(2), pp159-169. https://doi.org/10.6010/geoinformatics1990.2.2_159

[40] Moon, W. M., Chung, C. J. F., & An, P. (1991). Representation and integration of geological, geophysical and remote sensing data. Geoinformatics, *2*(2), 177-182. https://doi.org/10.6010/geoinformatics1990.2.2_177

[41] Derakhshani, R., & Mehrabi, A. (2009). Geologically-constrained fuzzy mapping of porphyry copper mineralization potential, Meiduk district, Iran: Trends in Applied Sciences Research, v4/4, pp 229-40. https://scialert.net/abstract/?doi=tasr.2009.229.240

[42] Ebadi, S., Valadanzoej, J., & Vafacinezhad, A. (2001). Evaluation of indexing Overlay. Fuzzy Logic and Genetic Algorithm Method for Industrial Estate Site Selection in GIS Environment, Tehran, Iran. https://www.researchgate.net/publication/237354937_Evaluation_of_Indexing_Overlay_Fuzzy_Logic_and_Genetic_Algorithm_Methods_for_Industrial_Estates_Site_Selection_in_GIS_Environment

[43] Esmailzadeh, M., Imamalipour, A., & Aliyari, F. (2022). Application of Fuzzy Gamma Operator to Generate Mineral Prospectivity Mapping for Cu-Mo Porphyry Deposits (Case Study: Kighal-Bourmolk Area, Northwestern Iran): Journal of Mining and Environment, v13(1), pp129-153. https://doi.org/10.22044/jme.2022.11218.2103

[44] Garrett, S., Griesbach, S., Johnson, D., Jones, D., Lo, M., Orr, W., & Sword, C. (1997). Earth model synthesis. *First break*, *15*(1). P 13-22. https://doi.org/10.3997/1365-2397.1997001

[45] Harris, D., & Pan, G. (1999). Mineral favorability mapping: a comparison of artificial neural networks, logistic regression, and discriminant analysis: Natural Resources Research, v8, pp 93-109. https://doi.org/10.1023/A:1021886501912

[46] Harris, J. R., Wilkinson, L., & Grunsky, E. C. (2000). Effective use and interpretation of lithogeochemical data in regional mineral exploration programs: application of Geographic Information Systems (GIS) technology: Ore Geology Reviews, v16(3-4), pp107-143. https://doi.org/10.1016/S0169-1368(99)00027-X

[47] Harris, D., Zurcher, L., Stanley, M., Marlow, J., & Pan, G. (2003). A comparative analysis of favorability mappings by weights of evidence, probabilistic neural networks, discriminant analysis, and logistic regression. Natural Resources Research, 12, 241-255. https://doi.org/10.1023/B:NARR.0000007804.27450.e8

[48] Harris, J. R., Grunsky, E., Behnia, P., & Corrigan, D. (2015). Data-and knowledge-driven mineral prospectivity maps for Canada's North: Ore Geology Reviews, v71, pp788-803. https://doi.org/10.1016/j.oregeorev.2015.01.004

[49] Kemp, L. D., Bonham-Carter, G. F., Raines, G. L., & Looney, C. G. (2001). Arc-SDM: ArcView Extension for Spatial Data Modeling Using Weights of Evidence. Logistic Regression, Fuzzy Logic and Neural Network Analysis. http://ntserv.gis.nrcan.gc.ca/sdm/

[50] Kumar, Pramod, & Pandey, Pradeep (2022). Mineral Exploration Scenario in India: Prospect, Promise and Policy Reforms: Journal of the Geological Society of India, v98(8), pp1178-1181. https://doi.org/10.1007/s12594-022-2141-8

[51] Liu, Y., Cheng, Q., Xia, Q., & Wang, X. (2014). Mineral potential mapping for tungsten polymetallic deposits in the Nanling metallogenic belt, South China: Journal of Earth Science, v25, pp689-700. https://doi.org/10.1007/s12583-014-0466-y

[52] Lunden, B., Wang, G., & Wester, K. (2001). A GIS based analysis of data from Landsat TM, airborne geophysical measurements, and digital maps for geological remote sensing in the Stockholm region, Sweden: International Journal of Remote Sensing, v22(4), pp517-532. https://doi.org/10.1080/01431160050505838

[53] Ma, Y., Zhao, J., Sui, Y., Liao, S., & Zhang, Z. (2020). Application of knowledge-driven methods for mineral prospectivity mapping of polymetallic sulfide deposits in the southwest Indian ridge between 46 and 52 E: Minerals, v10(11), pp970. https://doi.org/10.3390/min10110970

[54] McGaughey, W. J., & Vallee, M. A. (1998). Integrating geology and borehole geophysics in a common earth model for improved three-dimensional delineation of mineral deposits. Exploration and Mining Geology, 7(1-2), 51-62. GeoRef, Copyright 2004, American Geological Institute.

[55] Ministry of Mines, Govt. of India (2023). National Mineral Scenario report. Availalbe from: https://mines.gov.in/webportal/nationalmineralscenario

[56] Ministry of Mines, Govt. of India, (June 2023). Report of the committee on Critical Minerals for India. Available from: https://mines.gov.in/admin/storage/app/uploads/649d4212cceb01688027666.pdf

[57] Mohammadi, F., Tangestani, M. H., & Tayebi, M. H. (2022). Prospectivity mapping of orogenic lode gold deposits using fuzzy models: a case study of Saqqez area, NW of Iran: Earth Science Informatics, v15(4), pp2387-2404. https://doi.org/10.1007/s12145-022-00803-w

[58] Moon, W. M. (1990). Integration of geophysical and geological data using evidential belief function. IEEE Transactions on Geoscience and Remote Sensing, 28(4), 711-720.

[59] Nykänen, V., & Salmirinne, H. (2007). Prospectivity analysis of gold using regional geophysical and geochemical data from the Central Lapland Greenstone Belt, Finland: Geological Survey of Finland, v44, pp 251-269. https://www.researchgate.net/publication/228370685_Prospectivity_Analysis_of_Gold_Using_Regional_Geophysical_and_Geochemical_Data_from_the_Central_Lapland_Greenstone_Belt_Finland

[60] Nykänen, V., Lahti, I., Niiranen, T., & Korhonen, K. (2015). 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 Geology Reviews, 71, 853-860. https://doi.org/10.1016/j.oregeorev.2014.09.007

[61] Nykänen, V., Niiranen, T., Molnár, F., Lahti, I., Korhonen, K., Cook, N., & Skyttä, P. (2017). Optimizing a knowledge-driven prospectivity model for gold deposits within Peräpohja Belt, Northern Finland. Natural Resources Research, *26*, 571-584. https://doi.org/10.1007/s11053-016-9321-4

[62] Ping, An, Moon, W. M., & Rencz, A.,(1991). Application of fuzzy set theory to integrated mineral exploration. Can. Jour. Of explo. Geophysics, v27no1 p 1-11.

[63] Porwal, A., Carranza, E. J. M., & Hale, M. (2003). Artificial neural networks for mineral-potential mapping: a case study from Aravalli Province, Western India. Natural resources research, 12, 155-171. https://doi.org/10.1023/A:1025171803637

[64] Porwal, A., Carranza, E. J. M., & Hale, M. (2004). A hybrid neuro-fuzzy model for mineral potential mapping. Mathematical geology, 36(7), 803-826. https://doi.org/10.1023/B:MATG.0000041180.34176.65

[65] Porwal, A., Carranza, E. J. M., & Hale, M. (2006). Bayesian network classifiers for mineral potential mapping. Computers & Geosciences, 32(1), 1-16. https://doi.org/10.1016/j.cageo.2005.03.018

[66] Porwal, A., Das, R.D., Chaudhary, B., Gonzalez-Alvarez, I. and Kreuzer, O. (2015). Fuzzy inference systems for prospectivity modeling of mineral systems and a case-study for prospectivity mapping of surficial Uranium in Yeelirrie Area, Western Australia: Ore Geol. Rev., v.71, pp.839-852. https://doi.org/10.1016/j.oregeorev.2014.10.016

[67] Poulton, M. M., Sternberg, B. K., & Glass, C. E. (1992). Location of subsurface targets in geophysical data using neural networks. Geophysics, 57(12), 1534-1544. https://doi.org/10.1190/1.1443221

[68] Raines, G. L. (1999). Evaluation of weights of evidence to predict epithermal-gold deposits in the Great Basin of the Western United States. Natural Resources Research, 8(4), 257-276. https://doi.org/10.1023/A:1021602316101

[69] Saadat, S. (2017). Comparison of various knowledge-driven and logistic-based mineral prospectivity methods to generate Cu and Au exploration targets Case study: Feyz-Abad area (North of Lut block, NE Iran): Journal of Mining and Environment, v8(4), pp611-629. https://doi.org/10.22044/jme.2017.5345.1349

[70] Sabbaghi, H., & Tabatabaei, S. H. (2022). Application of the most competent knowledge-driven integration method for deposit-scale studies: Arabian Journal of Geosciences, v15(11), pp1057. https://doi.org/10.1007/s12517-022-10217-z

[71] Sadeghi, B., Khalajmasoumi, M., Afzal, P., & Moarefvand, P. (2014). Discrimination of iron high potential zones at the zaghia iron ore deposit, bafq, using index overlay GIS method. Iranian Journal of Earth Sciences, 6(2), 91-98. Available on Google Scholar.

[72] Singer, D. A., & Kouda, R. (1997). Use of a neural network to integrate geoscience information in the classification of mineral deposits and occurrences. In Proceedings of exploration (Vol. 97, pp. 127-134).

[73] Singer, D. A., & Kouda, R. (1999). A comparison of the weights-of-evidence method and probabilistic neural networks. Natural Resources Research, *8*, 287-298. https://doi.org/10.1023/A:1021606417010

[74] Singh P. K., and Jha Ranjeeta (2020): Predictive modelling for gold potential mapping with the spatial integration of geoscientific data in GIS environment for parts of Mahakoshal Group in UP, India: Indian Journal of Geosciences, v74, no-1.

[75] Sun, T., Li, H., Wu, K., Chen, F., Zhu, Z., & Hu, Z. (2020). Data-driven predictive modelling of mineral prospectivity using machine learning and deep learning methods: A case study from southern Jiangxi Province, China: Minerals, v10(2), pp102. https://doi.org/10.3390/min10020102

[76] Tangestani, M. H., & Moore, F. (2001). Porphyry copper potential mapping using the weights of evidence model in a GIS, northern Shahr e Babak, Iran: Australian Journal of Earth Sciences, v48(5), pp695-701. https://doi.org/10.1046/j.1440-0952.2001.485889.x

[77] Venkataraman, G., Madhavan, B. B., Ratha, D. S., Antony, J. P., Goyal, R. S., Banglani, S., & Roy, S. S. (2000). Spatial modeling for base-metal mineral exploration through integration of geological data sets: Natural Resources Research, v9(1), pp 27-42. https://doi.org/10.1023/A:1010157613023

[78] Wolfgang N. (2001). Images of the invisible-prospection methods for the documentation of threatened archaeological sites. Naturwissenschaften, *88*, 13-24. https://doi.org/10.1007/s001140000192

[79] Yeomans, C. M., Shail, R. K., Grebby, S., Nykänen, V., Middleton, M., & Lusty, P. A. (2020). A machine learning approach to tungsten prospectivity modelling using knowledge-driven feature extraction and model confidence: Geoscience Frontiers, v11(6), pp2067-2081. https://doi.org/10.1016/j.gsf.2020.05.016

[80] Zadeh, L. A. (1965). Fuzzy sets, Information and control, v8(3), pp338-353. http://dx.doi.org/10.1016/S0019-9958(65)90241-X

[81] Zimmermann, H.J. (1985). Fuzzy set theory and its applications. Springer Science Buisness Media, LLC. A Book.

[82] Zhang, N., & Zhou, K. (2015). Mineral prospectivity mapping with weights of evidence and fuzzy logic methods: Journal of Intelligent & Fuzzy Systems, v29(6), pp2639-2651. https://doi.org/10.3233/IFS-151967

[83] Zuo, R., & Carranza, E. J. M. (2011). Support vector machine: A tool for mapping mineral prospectivity: Computers & Geosciences, 37(12), 1967-1975. https://doi.org/10.1016/j.cageo.2010.09.014