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Research on an Intelligent Prospecting Workflow for Bauxite Deposits: Integrating AI Prediction with Surpac 3D Visualization

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Abstract

The exploration for concealed bauxite deposits presents significant challenges for traditional methods. This paper proposes a novel intelligent prospecting workflow that seamlessly integrates artificial intelligence (AI) prediction with professional three-dimensional (3D) visualization and analysis in Surpac. The workflow begins with the systematic processing and standardization of multi-source geospatial data, including geological maps, geophysical data, and remote sensing imagery, into a unified gridded format. This data serves as input for machine learning models, such as Random Forest, which are trained on known mineral occurrences to generate a predictive mineral prospectivity map. The core innovation lies in the closed-loop workflow where the AI-generated prospectivity model, exported as an ASCII grid file, is directly imported into Surpac. Within Surpac's powerful 3D environment, geologists can dynamically visualize the probability model fused with other geological data, perform interactive 3D interpretation, and delineate exploration targets. This integration creates a synergistic cycle where quantitative AI-driven insights directly inform qualitative spatial reasoning and decision-making within a robust 3D platform, significantly enhancing the efficiency and effectiveness of bauxite exploration.

Keywords

Bauxite Prospecting; Intelligent Workflow; Artificial Intelligence (AI); 3D Visualization; Surpac; Mineral Prospectivity Mapping

1. Introduction

Bauxite, the primary ore for aluminum, is a strategically critical mineral resource. In China, the majority of bauxite deposits are of the sedimentary type, often controlled by complex paleogeographic and structural factors, with orebodies lying atop karst unconformities. As exploration increasingly targets deep-seated and concealed orebodies, traditional, experience-dependent prospecting methods face severe limitations in dealing with this complexity.

Artificial Intelligence (AI), particularly machine learning (ML), has emerged as a powerful tool for mineral prospectivity mapping (MPM). ML algorithms can identify complex, non-linear relationships between multi-source geological data and known mineral occurrences, enabling data-driven predictive modeling [1]. However, a significant gap often exists between the generation of these predictive 2D maps and their practical application by geologists. The results are frequently disconnected from the three-dimensional (3D) geological context that is essential for understanding ore-forming processes and making exploration decisions .

Conversely, professional 3D mining software like Surpac provides an unparalleled environment for constructing, visualizing, and analyzing complex geological models. Yet, its analytical capabilities are often based on deterministic interpolation and lack the predictive, data-driven power of modern AI models.

This paper aims to bridge this gap by proposing a closed-loop intelligent prospecting workflow. This workflow systematically connects multi-source data input, AI-powered predictive modeling, and 3D visualization and interpretation within Surpac. The objective is to move beyond isolated AI predictions and create an integrated environment where quantitative computational insights directly enhance and are validated by qualitative 3D spatial reasoning, forming a synergistic cycle for bauxite exploration.

2. Overall Workflow Architecture

The proposed intelligent workflow is designed as a sequential yet iterative process, where the output of one stage directly feeds into the next, ultimately creating a feedback loop for continuous refinement. The entire process can be conceptualized in three main stages: Data Preparation and Standardization, AI-Driven Predictive Modeling, and 3D Integration and Interpretation in Surpac. The seamless flow between these stages, particularly the critical handover of the AI results to the 3D environment, is the cornerstone of this methodology. The following diagram illustrates this integrated architecture and the flow of data and results.

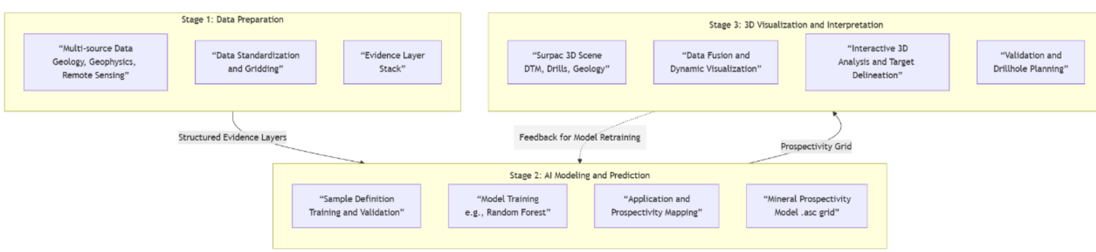

Figure 1. Architecture of the integrated AI-Surpac prospecting workflow

The workflow initiates with Data Preparation (Stage 1), where all relevant geospatial data is collected and transformed into a consistent, gridded format. This creates a multi-dimensional data cube of evidence layers. This structured data is then passed to AI Modeling & Prediction (Stage 2), where ML models are trained and applied to generate a quantitative mineral prospectivity map, exported as a portable ASCII grid file. This file is the key deliverable that bridges the AI world with the 3D world. In 3D Visualization & Interpretation (Stage 3), this grid is imported into Surpac, where it is fused with existing 3D data. Geologists then actively interpret this integrated scene, using Surpac's tools to analyze the AI results in their proper spatial context and delineate concrete exploration targets. The dashed line from Stage 3 back to Stage 2 represents the crucial feedback loop, where insights gained from 3D interpretation can inform the refinement of future AI models.

3. Data Preparation: Building the Evidence Cube

The foundation of any robust AI model is high-quality, consistently prepared input data. For bauxite prospecting, the required data spans several domains, each providing unique insights into the ore-forming system. The critical challenge lies in harmonizing these diverse datasets into a unified spatial framework suitable for grid-based computation.

Geological map data provides the foundational context. Key layers, such as the distribution of specific ore-hosting strata (e.g., the Benxi Formation), are converted into distance-to-layer grids. This allows the AI model to quantify the spatial relationship between any location and a favorable geological unit. Similarly, faults and lineaments are converted into distance grids, as these structures often control paleo-topography or fluid flow. Geophysical data, including aeromagnetic and gravity surveys, provides insights into the sub-surface architecture. Processed magnetic data can highlight intrusive rocks and basement structures, while gravity data can reveal basement relief, which is critical for reconstructing the paleogeographic setting favorable for bauxite accumulation [2]. These datasets are typically already gridded and are resampled to a common cell size.

Remote sensing data is pivotal for extracting surface alteration minerals. Multispectral sensors like ASTER and Landsat-8 are processed using specialized algorithms (e.g., band ratios, principal component analysis) to generate maps of ferric-iron alteration (limonitization) and argillic alteration (kaolinitization, halloysitization), which are key hallmarks of bauxite mineralization [3]. A Digital Elevation Model (DEM) and its derivatives (slope, curvature) are also incorporated as they can reflect modern weathering patterns and remnants of paleo-landforms.

Finally, geochemical data, such as stream sediment samples, provide direct chemical indicators. Elements like Al, Fe, Ga, and Li are interpolated to create geochemical anomaly maps. The culmination of this stage is a stack of raster layers, all perfectly aligned in terms of geographic extent and cell size. Each grid cell now possesses a unique vector of attributes—distance to fault, magnetic intensity, alteration intensity, geochemical value—that collectively describe its geological character. This "evidence cube" is the direct input for the AI modeling stage.

4. AI-Driven Predictive Modeling

The AI component acts as the analytical engine of the workflow, tasked with learning the complex signature of bauxite mineralization from the prepared evidence layers. The goal is to translate the multi-dimensional evidence cube into a single, interpretable map of mineral prospectivity.

The process begins with sample definition. Known bauxite occurrences are used as positive training samples, representing points where the ore-forming process was successful. An equal number of negative samples are strategically selected from areas deemed barren based on geological knowledge or previous exploration. This creates a balanced dataset for the model to learn from. A machine learning algorithm, such as Random Forest, is then trained on this data [3]. The Random Forest algorithm builds an ensemble of decision trees, each trained on a random subset of the data and features. During training, the model inherently performs feature importance analysis, quantitatively ranking the evidence layers based on their contribution to predicting the known mineral occurrences. This output is itself a valuable result, providing a data-driven assessment of which geological factors are most critical for bauxite formation in the study area.

Once trained and validated, the model is applied to every cell in the evidence cube across the entire study area. For each cell, the model computes a probability value between 0 and 1, representing the likelihood of that cell hosting a bauxite deposit based on its multi-attribute geological signature. The output is a continuous Mineral Prospectivity Map, where every pixel holds a predictive probability value. This final grid is exported in the widely supported ASCII Grid (.asc) format. This simple text-based format contains a header with spatial reference information followed by the matrix of probability values, making it an ideal, portable vessel for transferring the AI's findings into the Surpac environment for 3D visualization.

5. 3D Integration and Closed-Loop Interpretation in Surpac

The integration of the AI-generated prospectivity map into Surpac is where the predictive model transitions from a abstract map into a practical exploration tool, enabling a truly closed-loop workflow. This stage focuses on 3D contextualization, interactive validation, and target generation.

The process begins by importing the .asc file into Surpac as a **grid surface**. This prospectivity surface is then dynamically draped over the high-resolution Digital Terrain Model (DTM) within Surpac's 3D scene. The powerful rendering engine of Surpac allows for immediate and intuitive visualization. Geologists can apply a color ramp—for instance, using a red-to-blue scheme where red indicates high probability and blue indicates low probability—and adjust the transparency of the prospectivity layer. This allows the "hot" prospective zones to visually stand out while remaining visually integrated with the underlying topography and other geological data, such as drilled boreholes, geological boundary wireframes, and structural models.

This 3D fusion enables **interactive spatial analysis** that is impossible in 2D. A geologist can rotate, zoom, and fly through the scene, examining the relationship between high-probability zones and specific geological features from any angle. They can use Surpac's sectioning tools to slice through the 3D probability volume and create cross-sections, analyzing how the prospectivity evolves with depth. This direct interaction facilitates the **validation of the AI model's output** against the geologist's domain knowledge. If high-probability areas align well with understood geological controls, confidence in the model increases. Conversely, discrepancies can be investigated, potentially leading to new geological hypotheses.

The culmination of this stage is **interactive 3D target delineation**. Based on the 3D visualization and analysis, geologists can use Surpac's digitization tools to manually outline the most promising areas or use its analytical functions to automatically extract cells above a certain probability threshold (e.g., $P > 0.75$). These are then saved as 3D wireframe objects, representing the final **exploration targets**. These target wireframes can be used for volumetric calculations and, most importantly, for designing and planning subsequent exploration activities, such as drillhole trajectories.

This entire process forms a **closed loop**. The insights gained from the 3D interpretation in Surpac—such as which features the model predicted well or which it missed—provide invaluable qualitative feedback. This feedback can be used to refine the AI model in the next iteration, for example, by adjusting the training samples, incorporating new evidence layers suggested by the 3D analysis, or tuning model parameters. This creates a virtuous cycle of continuous improvement, tightly coupling machine intelligence with human expertise.

6. Conclusion

This paper has presented a comprehensive and integrated intelligent workflow for bauxite prospecting that effectively bridges the gap between data-driven AI prediction and professional 3D geological visualization. The workflow establishes a clear, sequential pathway from multi-source data standardization through to the generation of concrete 3D exploration targets within the Surpac platform. Its most significant contribution is the creation of a **closed-loop system** where the quantitative power of AI and the qualitative, spatial reasoning capabilities of geologists are not isolated but are synergistically combined.

The key to this integration is the portable ASCII grid format, which acts as a universal adapter, allowing the AI-generated prospectivity model to be seamlessly absorbed into the sophisticated 3D visualization and analysis environment of Surpac. This enables more than just visualization; it enables true **3D contextualization and validation** of the model's output. The dynamic and interactive nature of Surpac empowers geologists to interrogate the AI's findings from multiple perspectives, leading to more confident and geologically sound target delineation.

Looking forward, this workflow provides a flexible framework that can be extended and enhanced. Future work will involve the integration of **Explainable AI (XAI)** techniques to make the model's decision-making process more transparent to geologists, thereby building greater trust and facilitating deeper geological insight. Furthermore, embedding this workflow into a **cloud-based platform** could streamline data management, computation, and collaboration, making intelligent prospecting more accessible and efficient. This research demonstrates a practical and powerful path forward for modern mineral exploration, where human and machine intelligence coalesce to tackle the challenge of finding the resources of the future.

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