

# ἀρχαῖος (Archaïos): Archeological Discovery Using OpenAI Models.

## PROJECT OVERVIEW

The ARCHAÏOS project discovered 126 extreme confidence archaeological sites in Acre, Brazil, all located 20-160km from water sources - an unprecedented pattern that challenges fundamental archaeological assumptions. Using multi-evidence AI fusion, we achieved 100% validation rate from expert review despite the water anomaly.

### Key Links:

- [GitHub Repository](#) , [Submission Notebook](#) , Full Writeup

## METHODOLOGY PIPELINE

### 1. Data Integration & Feature Engineering

- 28,031 H3 hexagons (~4.6 km<sup>2</sup> each) covering Acre state
- 65 raster features: elevation, vegetation indices, topographic position
- Enhanced features: water distance, indigenous territories, forest status
- Known sites integration: 500+ geoglyphs from fernandosr85's datasets

### 2. CNN Earthwork Detection

- Architecture: 4-channel input (LRM500, TPI-100/250/500, elevation range)
- Training: Positive/negative sampling with archaeological potential weighting
- Performance: 97.9% ROC AUC on validation set

### 3. LLM Archaeological Reasoning

- Model: GPT-4o-mini with specialized prompts
- Analyzed: 4,205 high-potential sites
- Context: Topographic, spatial, and environmental features
- Output: Archaeological probability with reasoning chains

### 4. Multi-Evidence Fusion (Dempster-Shafer)

$$S_{\text{fused}} = \Sigma(w_i \times e_i \times c_i) / \Sigma(w_i)$$

Weights: CNN (0.30), LLM (0.30), Archaeological Score (0.15),  
Hydro (0.10), Spatial (0.05), Topo (0.05), Cultural (0.05)

### 5. Water Anomaly Enhancement

$$S_{\text{final}} = S_{\text{fused}} \times \alpha(d_w) \times \beta(c_{\text{cultural}})$$

$$\alpha(d_w) = 1.1 \text{ if } d_w > 20\text{km and } S_{\text{fused}} > 0.85, \text{ else } 1.0$$

$$\beta(c_{\text{cultural}}) = 1.05 \text{ if in indigenous territory, else } 1.0$$

## SCORING RUBRIC FOR AI ARCHAEOLOGICAL DISCOVERY

Our framework provides a rigorous scoring system that, when utilized with data from known sites, can be used for reinforcement fine-tuning of reasoning models on archaeological discovery tasks.

### Archaeological Evidence Quality Score:

$$Q_{\text{evidence}} = (1/m) \sum [\delta_j \times \gamma_j \times \text{sigmoid}(v_j - \theta_j)]$$

Where:

- $\delta_j$  = detection strength for feature  $j$
- $\gamma_j$  = geometric regularity score
- $v_j$  = vegetation anomaly index
- $\theta_j$  = threshold for feature  $j$

### Water Anomaly Severity Score:

$$A_{\text{water}} = \log(d_{\text{site}}/d_{\text{typical}}) \times (1 - e^{(-\lambda \times d_{\text{site}})})$$

Where:

- $d_{\text{site}}$  = distance to water (km)
- $d_{\text{typical}}$  = 3km (normal settlement distance)
- $\lambda$  = 0.02 (decay parameter)

### Comprehensive Site Validation:

$$V_{\text{site}} = (S_{\text{final}} \times Q_{\text{evidence}}) / (1 + \sigma \times A_{\text{water}}) \times \prod (1 + \epsilon_k)$$

Where:

- $\sigma$  = 0.1 (water penalty factor - allows anomalies)
- $\epsilon_k$  = boost factors for additional evidence

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## REINFORCEMENT LEARNING FRAMEWORK

### Reward Function for Archaeological Reasoning Models:

$$R(s,a) = r_{\text{discovery}} + r_{\text{evidence}} + r_{\text{reasoning}} - p_{\text{false}}$$

```

r_discovery = {
    +100 if validated by expert
    +50  if high confidence & clustered
    +10  if moderate confidence
    0    otherwise
}

```

$$r_{\text{evidence}} = \sum [w_i \times I(e_i > \tau_i) \times \log(1 + e_i)]$$

$$r_{\text{reasoning}} = \alpha \times \text{CosineSim}(r_{\text{generated}}, r_{\text{expert}}) + \beta \times \text{Perplexity}^{(-1)}$$

```

p_false = {
    -200 if proven non-archaeological
    -50  if low evidence quality
    -20  if isolated & low confidence
}

```

### State Representation:

$$s = [f_{\text{spatial}}, f_{\text{spectral}}, f_{\text{topographic}}, f_{\text{contextual}}, d_{\text{water}}, h_{\text{history}}]$$

## GRADING FRAMEWORK FOR MODEL EVALUATION

### Performance Metrics:

$$P_{\text{model}} = (1/N) \sum [\omega_1 \times \text{TPR} + \omega_2 \times \text{PPV} + \omega_3 \times F_{\beta} + \omega_4 \times D_{\text{anomaly}}]$$

Difficulty-Adjusted Scoring:

$$S_{\text{adjusted}} = S_{\text{base}} \times (1 + \sum [\mu_j \times I(\text{challenge}_j \text{ met})])$$

Challenge Multipliers:

- Water distance >50km:  $\mu_1 = 0.3$
- Dense canopy:  $\mu_2 = 0.2$
- No surface features:  $\mu_3 = 0.25$
- Multi-evidence convergence:  $\mu_4 = 0.15$

## KEY INNOVATIONS & TECHNIQUES

**1. Anomaly-Aware Fusion** Unlike traditional approaches that penalize sites far from water, our system recognizes when multiple evidence streams converge despite anomalies, enabling paradigm-shifting discoveries.

### 2. Hierarchical Validation

- Individual hexagon scoring
- Spatial clustering analysis

- Complex-level aggregation
- Expert review validation

**3. Explainable AI Pipeline** Every detection includes reasoning chains, evidence weights, and confidence measures - crucial for archaeological credibility and model improvement.

## RESULTS & IMPACT

### Discoveries:

- 126 sites with fused\_score  $\geq 0.95$
- All located 20-160km from water
- 18 major complexes identified
- 100% validation rate (50 sites reviewed)

**For Reinforcement Learning:** This scoring framework, when utilized with data from known archaeological sites, provides:

- Objective reward signals for discovery
- Difficulty-adjusted performance metrics
- Anomaly recognition capabilities
- Multi-evidence reasoning evaluation

**Scientific Significance:** The water anomaly pattern suggests:

- Unknown water management technologies
- Different settlement patterns than assumed
- New chapter in Amazonian archaeology

## IMPLEMENTATION & REPRODUCIBILITY

All code, data processing pipelines, and scoring functions are available in our GitHub repository. The framework is designed to be:

- **Modular:** Each component can be improved independently
- **Scalable:** Applicable to other regions and time periods
- **Trainable:** Provides clear signals for RL model improvement
- **Generalizable:** This approach can be generalized for any site.

When utilized with verified archaeological data, this framework enables reinforcement fine tuning of reasoning models to recognize both conventional patterns and paradigm-shifting anomalies - essential for advancing archaeological AI.