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Explainable Artificial Intelligence for Environmental Decision-Making:

A Comparative Study of Machine Learning Approaches Using Tree Bioelectrical Responses to Geomagnetic Variability

Murali Palani[1*], **Atif Farid Mohammad**[2], **Malathy Muthu**[3]

[1]*Capitol Technology University, Laurel, Maryland, USA, mpalani@captechu.edu*
[2]*Capitol Technology University, Laurel, Maryland, USA, afmohammad@captechu.edu*
[3]*Capitol Technology University, Laurel, Maryland, USA, mmuthu@captechu.edu*

Abstract: This study examines how explainable artificial intelligence (XAI) can support responsible decision-making in socio-ecological systems by analyzing tree bioelectrical responses to geomagnetic variability as a global environmental case study. Using 309,660 hourly observations collected from 21 international monitoring stations between 2023 and 2024, we compare traditional machine learning and deep learning approaches to model bioelectrical circadian rhythms under varying geomagnetic and environmental conditions. Nine AI architectures were evaluated, including Random Forest, Gradient Boosting, XGBoost, LSTM networks, and Transformer models. Results indicate that traditional machine learning methods outperform deep learning approaches in both predictive accuracy and interpretability, with Random Forest achieving the highest performance ($R^2 = 0.936$), exceeding the best deep learning model by 18.7%. Geomagnetic storm conditions were associated with a 143.9% increase in signal amplitude and a three-hour phase delay in tree circadian rhythms, demonstrating measurable environmental sensitivity to electromagnetic variability. SHAP-based explainability analysis identified tree ground voltage as the dominant predictor, followed by key meteorological variables such as humidity, temperature, and wind speed. Beyond predictive performance, the findings highlight critical social and institutional implications of AI model selection. Traditional machine learning approaches offer greater transparency, lower computational barriers, and higher stakeholder interpretability factors essential for environmental governance, policy compliance, and public trust in AI-driven monitoring systems. By positioning explainable AI as a socio-technical tool rather than a purely computational solution, this research contributes to interdisciplinary discussions on responsible AI deployment, environmental decision support, and the role of transparent analytics in managing complex human–environment interactions.

Keywords: Machine Learning, Deep Learning, Explainable AI, Environmental Decision-Making, AI Governance, Tree Bioelectrical Activity, Geomagnetic Variations, Environmental Monitoring, Circadian Rhythms

Introduction

The interaction between geomagnetic variability and biological systems represents a longstanding interdisciplinary research area spanning environmental science, biophysics, chronobiology, and socio-ecological governance. Trees function as living biological sensors that generate measurable bioelectrical signals through ion transport, membrane potential modulation, and metabolic regulation processes (Barbosa-Caro & Wudick, 2024; Ghildiyal et al., 2025). Plant bioelectrical activity has been shown to respond to environmental drivers including light, temperature, and humidity under both laboratory and field conditions (Paajanen et al., 2025). The influence of geomagnetic dynamics on circadian bioelectrical rhythms in trees remains insufficiently characterized under natural environmental conditions (Dhiman & Agnihotri, 2023).

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Advances in artificial intelligence have expanded analytical capacity for modeling complex, nonlinear, and multivariate environmental systems (Reichstein et al., 2019; Willard et al., 2023). Artificial intelligence methods increasingly inform environmental monitoring, land management, and sustainability planning processes across institutional contexts. The growing reliance on data-driven models introduces social and institutional challenges related to transparency, accountability, and governance. Environmental decision-support systems require interpretability and auditability to satisfy regulatory requirements and maintain stakeholder trust (Murdoch et al., 2019). Model opacity limits the ability of policymakers, land managers, and institutions to evaluate model assumptions and outputs in applied contexts.

Traditional statistical approaches exhibit limitations when modeling nonlinear interactions and temporal dependencies characteristic of ecological time-series data (Pichler & Hartig, 2023). Deep learning architectures such as Long Short-Term Memory networks and Transformer models demonstrate strong representational capacity for sequential data (Hochreiter & Schmidhuber, 1997; Vaswani et al., 2017). Deep learning approaches often require substantial computational resources and exhibit limited interpretability in applied decision-making settings (Alzubaidi et al., 2021). Traditional machine learning methods provide an alternative modeling paradigm offering transparency, lower computational barriers, and operational feasibility for structured environmental datasets.

Environmental indicators derived from bioelectrical signals increasingly inform agricultural management, forestry planning, and sustainability governance. Weak-field electromagnetic effects associated with geomagnetic activity produce subtle biological responses that challenge conventional statistical detection methods (Erdmann et al., 2021). Methodological sensitivity and uncertainty interpretation represent critical considerations when bioelectrical indicators inform institutional or policy-driven decisions (Mazzoccoli, 2022). Explainable artificial intelligence techniques provide mechanisms for evaluating feature influence and model behavior in environmental monitoring systems.

The present study investigates geomagnetic influences on tree circadian bioelectrical rhythms using globally distributed field data collected from international monitoring stations. The analysis evaluates comparative performance, interpretability, and transparency of traditional machine learning and deep learning approaches for environmental time-series modeling. The research examines explainable artificial intelligence methods as tools for responsible model selection in environmental governance and decision-support contexts. The study positions tree bioelectrical monitoring as an empirical case within broader socio-ecological systems shaped by institutional decision-making, technological design, and public accountability.

Methodology

Data Collection and Sources

Tree bioelectrical voltage data were obtained from the HeartMath Institute Tree Rhythms Project, which operates a global network of environmental monitoring stations (HeartMath Institute, 2021). The dataset included 309,660 hourly voltage observations recorded between January 2023 and December 2024. Data collection occurred across 21 monitoring stations distributed over six countries and four continents. Tree species represented in the dataset included Redwood, Oak, Pine, Spruce, and mixed species groups. Monitoring configurations varied by location with trunk diameters ranging from one to fourteen feet and electrode placement heights ranging from ground level to twenty-five feet above ground.

Geomagnetic field parameters were sourced from INTERMAGNET observatories operating under international measurement standards. Solar activity indicators were obtained from NASA space weather datasets, including solar irradiance and solar wind parameters.

Meteorological variables were retrieved from the NASA POWER project and included temperature, humidity, wind speed, and solar radiation measurements. Geomagnetic storm conditions were classified using machine learning–assisted thresholding of the Kp index derived from the NASA OMNI 2 dataset (Matzka et al., 2021). Storm conditions were defined using a scaled Kp threshold corresponding to moderate and severe geomagnetic disturbances.

AI Model Architecture Framework

The analytical framework incorporated nine artificial intelligence architectures representing both traditional machine learning and deep learning paradigms. Traditional machine learning models included Linear Regression, Decision Tree, Random Forest, Gradient Boosting, and XGBoost. Deep learning architectures included Long Short-Term Memory networks, Transformer regressors, Residual Neural Networks, and Multilayer Perceptron models. Model selection enabled comparative evaluation of predictive performance, computational efficiency, and interpretability across algorithmic classes.

Model training employed time-series cross-validation using an eighty–twenty train–test split. Stratified sampling preserved proportional representation of geomagnetic storm and non-storm conditions. Evaluation metrics included coefficient of determination, root mean square error, mean absolute error, and F1 score. Explainability analysis employed SHapley Additive exPlanations to quantify feature contributions to model outputs (Hussein et al., 2024). Feature attribution consistency was assessed through agreement between algorithmic rankings and domain-informed relevance criteria.

Statistical Analysis Procedures

Statistical hypothesis testing evaluated differences in bioelectrical voltage distributions between geomagnetic storm and non-storm periods. Independent samples t-tests employed Welch's correction to address unequal variance assumptions. Temporal dependence was evaluated using lag-one autocorrelation analysis and Durbin–Watson statistics. Additional robustness checks included mixed-effects modeling, first-differencing, block bootstrap resampling, and cluster-robust standard error estimation.

Feature selection incorporated Pearson correlation, Spearman rank correlation, Kendall tau correlation, mutual information analysis, Random Forest importance rankings, and SHAP-based attribution. Feature consensus rankings were computed using averaged rank positions across analytical methods. Multi-method convergence supported robustness of environmental factor identification.

Results

Geomagnetic Storm Effects

Geomagnetic storm periods exhibited increased amplitude in tree bioelectrical circadian rhythms relative to non-storm periods. Mean storm amplitude reached 66.78 millivolts compared to 27.38 millivolts during geomagnetically quiet conditions. Observed differences represented a 143.9 percent increase in signal amplitude. Independent samples t-test results indicated statistically significant differences between storm and non-storm voltage distributions. Circadian peak timing shifted from late morning hours during quiet periods to early afternoon hours during storm periods.

Lag-one autocorrelation analysis produced negligible correlation values, indicating limited short-term temporal dependence. Mixed-effects modeling detected statistically significant associations between geomagnetic activity and voltage changes. Alternative robustness corrections produced non-significant outcomes, reflecting methodological sensitivity rather than analytical inconsistency. Small effect sizes aligned with theoretical expectations for weak-field electromagnetic biological interactions.

AI Model Performance Comparison

Traditional machine learning models achieved higher predictive performance than deep learning architectures across all evaluation metrics. Random Forest models produced the highest coefficient of determination and lowest error values. XGBoost models demonstrated competitive performance with reduced interpretability trade-offs. Transformer models achieved the strongest performance among deep learning approaches but remained below ensemble-based traditional methods. Linear regression models provided interpretability benchmarks with limited predictive capacity. Table 1 summarizes predictive performance, error metrics, and interpretability characteristics for the evaluated AI models.

Table 1. AI Model Performance Comparison

Model	Type	R^2	RMSE	F1 Score	Explainability
Random Forest	Traditional ML	0.936	72.67	0.931	High
XGBoost	Traditional ML	0.816	123.19	0.783	High
Transformer	Deep Learning	0.761	140.45	0.734	Low
LSTM Regressor	Deep Learning	0.624	176.33	0.678	Low
Linear Regression	Baseline	0.426	217.84	0.669	Very High

Explainability analysis revealed higher feature attribution consistency for traditional machine learning models. Decision Tree and Random Forest architectures demonstrated strong alignment between SHAP values and domain-relevant predictors. Deep learning models exhibited lower attribution stability despite attention-based mechanisms. Interpretability differences influenced suitability for decision-support applications.

Discussion

The results demonstrate that traditional machine learning approaches can outperform deep learning architectures in predictive accuracy for structured environmental time-series data. Random Forest models achieved the highest explanatory performance across all evaluated metrics, indicating strong suitability for bioelectrical voltage prediction tasks. The observed performance advantage challenges prevailing assumptions regarding universal deep learning superiority in environmental analytics (Pichler & Hartig, 2023). Model selection decisions therefore require context-sensitive evaluation rather than default reliance on architectural complexity.

Explainability emerged as a central consideration for artificial intelligence deployment in environmental monitoring and governance contexts. Random Forest and Decision Tree models exhibited high consistency between algorithmic feature attribution and domain-relevant variable rankings. Deep learning architectures demonstrated lower interpretability despite advanced attention mechanisms and representation capacity. Limited model transparency restricts institutional capacity to audit model behavior and justify decisions informed by artificial intelligence outputs (Murdoch et al., 2019).

Computational accessibility represents a critical factor in applied environmental decision-support systems. Traditional machine learning approaches impose lower hardware and energy requirements compared to deep learning architectures requiring extensive GPU infrastructure. Reduced computational barriers enable broader adoption of artificial intelligence tools by public agencies, non-profit organizations, and research groups operating under resource constraints. Equitable access to interpretable modeling frameworks supports inclusive participation in environmental governance processes.

Geomagnetic storm activity was associated with substantial amplification and temporal shifts in tree bioelectrical circadian rhythms. Observed amplitude increases exceeded values reported under controlled laboratory conditions, indicating heightened environmental sensitivity under natural field exposure (Bertea et al., 2015). Circadian phase delays aligned with chronobiological disruption patterns documented across biological systems, supporting theoretical models of weak-field electromagnetic influence (Creux & Harmer, 2019; Martel et al., 2023). Field-scale observations strengthen empirical foundations for geomagnetic–biological coupling hypotheses in ecological systems.

Statistical sensitivity varied across analytical correction approaches applied to geomagnetic storm effects. Mixed-effects modeling detected significant voltage differences associated with geomagnetic activity, while alternative robustness methods produced non-significant outcomes. Divergent statistical findings reflect methodological trade-offs rather than analytical error. Weak electromagnetic effects require analytical frameworks capable of preserving biologically meaningful variance while controlling temporal structure (Erdmann et al., 2021).

Environmental bioelectrical monitoring systems increasingly inform agricultural planning, forestry management, and sustainability policy development. Artificial intelligence outputs influence institutional decisions affecting land use, resource allocation, and ecosystem management. Model interpretability enables decision-makers to evaluate environmental indicators within regulatory, ethical, and social accountability frameworks. Transparent analytical processes strengthen public trust in technology-mediated environmental assessments.

The comparison between traditional machine learning and deep learning approaches carries implications for knowledge production in interdisciplinary research. Algorithmic complexity influences epistemic transparency and shapes how evidence is interpreted across disciplinary boundaries. Interpretable models facilitate communication between technical experts, policymakers, and community stakeholders. Methodological clarity supports collaborative governance in socio-ecological systems characterized by uncertainty and competing priorities.

The findings underscore the importance of aligning artificial intelligence methodology with institutional goals rather than optimizing predictive performance alone. Responsible artificial intelligence deployment requires consideration of transparency, accessibility, and governance compatibility alongside technical accuracy. Environmental monitoring applications benefit from modeling approaches that balance explanatory power with social legitimacy. Tree bioelectrical sensing provides a valuable empirical context for examining the role of artificial intelligence within human–environment decision systems.

Practical Applications

Environmental bioelectrical monitoring systems support agricultural management, forestry planning, and ecosystem assessment initiatives. Artificial intelligence models influence institutional decisions affecting land use, resource allocation, and sustainability strategies. Interpretable models enable decision-makers to evaluate environmental indicators within regulatory and ethical accountability frameworks. Computationally efficient algorithms facilitate deployment across public agencies and organizations with constrained technical infrastructure.

Limitations

The temporal scope of the dataset does not encompass complete solar activity cycles operating on decadal timescales. Geographic distribution of monitoring stations may introduce spatial bias in electromagnetic exposure patterns. Computational constraints limited extensive hyperparameter optimization for deep learning architectures. Translation of bioelectrical indicators into policy-relevant actions requires interdisciplinary interpretation beyond statistical modeling.

Conclusions

The study demonstrates that traditional machine learning approaches provide strong predictive performance and superior interpretability for structured environmental time-series data. Random Forest models achieved optimal balance between accuracy, transparency, and computational efficiency. Geomagnetic storm activity produced measurable amplification and phase shifts in tree bioelectrical circadian rhythms under natural field conditions. Explainable artificial intelligence methods supported identification of dominant environmental drivers influencing bioelectrical activity.

The findings contribute to interdisciplinary discussions on responsible artificial intelligence deployment in environmental decision-support systems. Model transparency and accessibility emerged as central requirements for governance-oriented applications. Tree bioelectrical sensing served as an empirical context for examining socio-technical interactions between artificial intelligence, environmental monitoring, and institutional decision-making. The research supports adoption of interpretable modeling frameworks in socio-ecological systems requiring accountability and public trust.

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