AI and GIS for Smarter Agriculture: An Adaptive Framework for Land Bonitation

This research introduces an integrated artificial intelligence and geospatial framework designed to modernize the traditional land bonitation process. Land bonitation, or land rating, has historically served as a foundation for agricultural assessment, resource allocation, and policy formulation. However, classical approaches rely on static coefficients and complete datasets, rendering them rigid and often obsolete under dynamic environmental conditions. This study proposes an adaptive, data-driven alternative that integrates Geographic Information Systems (GIS) with machine learning algorithms to predict and evaluate land productivity using incomplete or evolving data. By embedding deep learning forecasting models such as LSTM, GRU, and CNN within a GIS workflow, the framework enables spatial and temporal adaptability. This innovation represents a step toward intelligent agricultural management systems that combine predictive analytics with spatial visualization, empowering both researchers and policymakers to make evidence-based decisions grounded in real-time data and scientific precision.

Agriculture remains one of the most data-sensitive sectors, affected by complex interdependencies between soil, climate, and human activity. Traditional bonitation methods, developed in the mid-twentieth century, rely on exhaustive static datasets and fixed formulae that cannot adapt to temporal variation or incomplete data. In contrast, the modern agricultural landscape demands responsive systems capable of continuous adjustment based on climatic, topographic, and socioeconomic inputs. This study situates itself at the intersection of geoinformatics and artificial intelligence, proposing a hybrid methodology that compensates for data absence while maintaining methodological rigor. The incorporation of machine learning within GIS environments creates a scalable and modular framework that not only evaluates land quality but also forecasts its potential evolution. Thus, the introduction sets the premise for transforming bonitation into a dynamic, intelligent, and data-resilient process.

The core objective of this research is to develop a **GIS-integrated, machine learning–enhanced adaptive bonitation framework** that unifies predictive modeling and spatial analysis. Specifically, the framework aims to improve land quality assessment by forecasting critical environmental indicators, such as precipitation and temperature, and integrating these forecasts into spatial mapping tools. Through this adaptive approach, the bonitation coefficient (BC)—a quantitative index summarizing land potential—is recalibrated dynamically based on updated climate and soil inputs. The research also strives to bridge methodological gaps by enabling bonitation processes to operate even when data is incomplete or unevenly distributed across regions. A secondary goal is to enhance interpretability by generating high-resolution GIS visualizations of bonitation zones, providing policymakers and farmers with intuitive decision-support instruments. Ultimately, the project exemplifies how artificial intelligence can complement classical evaluation systems, transforming them into predictive, scalable, and scientifically grounded tools.

The proposed methodology combines three distinct yet interlinked components: (1) data forecasting through deep learning models, (2) bonitation coefficient computation, and (3) spatial interpolation using GIS. The framework utilizes 17 indicators—covering soil structure, climate variables, and topographic factors—to compute the bonitation coefficient. Missing or incomplete climate data are reconstructed using neural network architectures such as LSTM, GRU, and CNN, which excel at capturing nonlinear temporal dependencies. Each model is trained using historical data spanning 61 years (1960–2021), ensuring robustness and generalization. Forecasted climate indicators are then spatially integrated into GIS using Voronoi tessellation, a geometric interpolation method that divides territory into polygons based on proximity to observation points. This process yields high-resolution bonitation maps capable of representing both observed and predicted environmental conditions. The methodological design ensures that classical land evaluation logic is preserved while infusing it with AI-driven adaptivity and spatial intelligence.

Romania was selected as the test region due to its diverse topography, continental climate, and extensive agricultural history. The case study focused primarily on **precipitation forecasting**, as it represents one of the most critical and variable factors influencing land productivity. Historical precipitation data from WorldClim (1960–2021) served as the training corpus for three deep learning models—LSTM, GRU, and CNN—each calibrated to forecast multi-year precipitation trends. Results were evaluated using standard metrics such as the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The ensemble model, which combined the outputs of the individual networks, demonstrated superior performance, achieving $R^2 \approx 0.64$ and RMSE ≈ 18.8 mm. These findings confirm the feasibility of AI-based climate forecasting as an input for adaptive bonitation. The Romania case study illustrates how integrating spatial modeling with predictive learning can overcome regional data limitations and enhance land evaluation accuracy.

The results highlight the successful integration of predictive and spatial components within the proposed framework. Forecasting modules generated reliable estimates for missing climatic indicators, thereby expanding the applicability of the bonitation coefficient in regions with limited meteorological data. The Voronoi tessellation approach produced coherent, continuous spatial maps, facilitating the visual interpretation of bonitation levels across administrative units. The system's modular architecture allows users to update models as new data become available, ensuring long-term adaptability. Moreover, the combination of deep learning and GIS produced outputs that are not only statistically sound but also operationally interpretable, bridging the gap between computational complexity and field usability. These results collectively demonstrate that the integration of AI with traditional land evaluation frameworks can transform static agricultural assessment systems into adaptive, predictive, and policy-relevant tools.

The framework offers several methodological and practical advantages over conventional bonitation systems. First, it effectively addresses the problem of incomplete data, a pervasive issue in agricultural monitoring. By incorporating predictive modeling, the system can infer missing climatic variables without compromising accuracy. Second, the hybridization of classical evaluation principles with AI forecasting ensures methodological continuity, making the framework compatible with existing bonitation databases and policies. Third, the GIS integration enhances spatial resolution and interpretability, allowing decision-makers to visualize both current and projected land productivity patterns. Finally, the modular architecture ensures scalability—both geographically and computationally—enabling adaptation to diverse agricultural contexts worldwide. These advantages position the framework as a robust, future-ready tool that can support sustainable agricultural planning, climate adaptation, and resource optimization at local and national scales.

The study concludes that integrating artificial intelligence and GIS into the bonitation process provides a substantial methodological advancement in agricultural evaluation. The proposed system successfully combines the predictive capabilities of deep learning models with the spatial precision of GIS, resulting in an adaptive, data-driven, and context-aware framework. By forecasting key environmental indicators, the model compensates for data scarcity and enhances temporal responsiveness, while Voronoi-based spatial mapping ensures high interpretability. The framework's generalizability allows it to be transferred to other environmental and agricultural contexts, including soil fertility assessment, vegetation monitoring, and crop yield forecasting. Future research will focus on incorporating uncertainty quantification and integrating multi-sensor remote sensing data to further refine predictive precision. Overall, this approach demonstrates how interdisciplinary integration—linking AI, GIS, and environmental science—can lead to more resilient and intelligent agricultural systems aligned with modern sustainability objectives.