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Cedi Appreciation Relative to Fuel Prices - A Machine Learning and Ancient Geomantic Approach

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ABSTRACT

In recent years, the Ghanaian Cedi (GHS) has experienced notable appreciation against major global currencies, coinciding with fluctuating domestic fuel prices. Understanding the sustainability of this appreciation is crucial for policymakers, investors, and economic planners. This study adopts an innovative interdisciplinary approach by integrating Machine Learning (ML) techniques with principles from Ancient Geomancy, aiming to analyze and forecast the trajectory of the Cedi relative to fuel price dynamics. Quantitative analysis is conducted using historical exchange rate data and fuel pricing information, employing time series forecasting models such as Long Short-Term Memory (LSTM) networks, Random Forest Regression, and Prophet to predict future movements in the value of the Cedi. These models are evaluated using standard metrics including Root Mean Square Error (RMSE) and R-squared (R^2). Complementing the ML analysis, we apply symbolic and spatial interpretations from Ancient Geomantic traditions particularly those relating to elemental balance and directional energy flows to provide a qualitative framework for interpreting economic cycles and currency stability. The integration of these two paradigms allows for a richer, multi-dimensional understanding of economic phenomena. Our findings suggest that while Machine Learning models offer robust predictive capabilities, Geomantic insights contribute contextual depth, potentially revealing underlying patterns not captured through conventional quantitative methods alone. This study contributes to the growing discourse on blending traditional knowledge systems with modern computational tools in financial and economic analysis.

Keywords: Cedi appreciation, fuel prices, Machine Learning, Geomancy, economic forecasting, Ghanaian economy, LSTM, Random Forest, Prophet.

INTRODUCTION

In the past few weeks, the value of the Ghanaian currency, the Ghana Cedi (GH₵), has changed a lot (Bank of Ghana, 2023). Over the past few months, the Cedi has unexpectedly gained value against major global currencies like the US Dollar (USD) and the Euro (EUR). This is a change from a long-term trend of depreciation that started in 2020 (Agyapong et al., 2021; Quartey & Turkson, 2022). This rise in value is especially surprising because fuel prices at home are also going up, which has historically caused currency depreciation because it puts inflationary pressure on the economy (Ackah & Asomani, 2019; Amoani et al., 2020). The Ghana Statistical Service (2023) says that fuel prices have gone up by more than 40% in the last 18 months. This is mostly because of changes in the global oil market and taxes in Ghana. These are conditions that usually lead to lower investor confidence and capital outflows (Ofori-Abebrese et al., 2021).

Policymakers, financial analysts, and investors need to know what is going on behind this strange rise in value. Is it a short-term correction or a sign of deeper structural resilience? (Gockel et al., 2022). The link between fuel prices and exchange rates is complicated and affected by a number of macroeconomic factors, such as inflation, interest rates, the balance of payments, fiscal policy, and investor sentiment (Ghosh et al., 2016; Bahmani-Oskooee & Saha, 2019). Traditional econometric models like Vector Autoregression (VAR) and Autoregressive Distributed Lag (ARDL) often don't work well in emerging markets like Ghana, which have high volatility and structural weaknesses. This is because these models don't take into account the nonlinear and dynamic

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interactions between these variables (Adenutsi, 2011; Mensah & Tweneboah, 2020). Diks et al. (2011) say that linear models may not take into account regime shifts and feedback loops that happen a lot during times of economic instability.

To get around these problems, this study uses Machine Learning (ML) methods to model and predict how changes in the value of the Cedi will affect fuel prices. ML algorithms have been shown to work better than other methods on financial time series data that is high-dimensional, noisy, and non-linear (Hastie et al., 2009; Mullainathan & Spiess, 2017). We use Long Short-Term Memory (LSTM) networks, which are a type of recurrent neural network (RNN) that are good at finding long-term dependencies in sequential data (Hochreiter & Schmidhuber, 1997; Greff et al., 2015). We also use Random Forest Regression, which is known for being robust against overfitting and able to handle features that are different from each other (Breiman, 2001; Wihartiko et al., 2017), and Prophet, a model that Facebook made for predicting time series with strong seasonal patterns (Taylor & Letham, 2018). The Bank of Ghana (2023) and the World Bank (2023) provided the historical data that these models were trained on. It includes exchange rates, fuel prices, inflation, interest rates, and trade balances from 2015 to 2023.

This paper goes beyond traditional quantitative analysis by using ideas from Ancient Geomancy, a traditional way of interpreting space and symbols that has deep roots in African indigenous knowledge systems (Mbiti, 1990; Asante, 2003). Ifá (Yoruba), Sikidy (Malagasy), or Dakpɛ (Ewe) are some of the names for geomancy in different African cultures. It is based on the idea that natural and cosmic energies affect people's lives and the rhythms of society (Bascom, 1969; Ellis, 1890; Gyekye, 1996). To understand cycles of good luck, stability, and change, these systems often use symbolic arrangements, like the 16 main figures in Ifá divination (Idowu, 1962; Warnock, 2005). These kinds of epistemologies, which are often ignored in mainstream economic discussions, provide a qualitative, cyclical, and holistic way to understand economic events (Nkrumah, 1970; Wiredu, 1980).

We want to create a dual-lens analytical framework that combines computational forecasting with ancestral wisdom by comparing geomantic readings from traditional practitioners in the Ashanti and Ewe regions with the outputs of ML models (Odame, 2007; Nyamekye, 2021). For example, certain geomantic patterns linked to "stability" (like Oyeku in Ifá) or "flux" (like Ogbe) are linked to times when the currency goes up or down, respectively, to look for symbolic connections with economic cycles (Abimbola, 2005; Adewale, 2012). This method is similar to recent calls for epistemic pluralism in economics and development studies (Kuada, 2010; Mkandawire, 2005; Nnadozie, 2003), which stress how important it is to include local knowledge in scientific research.

This method from different fields helps not only with making better predictions about the economy in unstable emerging markets, but also with bigger discussions about how to decolonise knowledge production (Santos, 2014; wa Thiong'o, 1993; Ndlovu-Gatsheni, 2013). It questions the dominance of Western-centered models in finance and economics by showing that other ways of knowing are valid (Mafeje, 1971; Hountondji, 1997). It also responds to recent academic interest in hybrid epistemologies, which combine indigenous cosmologies and digital technologies to give new perspectives (Dei, 2014; Zuberi, 2004).

The main question this study tries to answer is whether the current value of the Ghana Cedi can last even though fuel prices keep going up and the economy as a whole is unstable. We look at both statistical probabilities and symbolic signs of economic resilience by comparing ML forecasts with geomantic readings. According to early results, ML models predict continued short-term appreciation due to more foreign investment and better trade balances (Bank of Ghana, 2023). However, geomantic readings show underlying energetic imbalances that could lead to future volatility, which is in line with the idea of karmic economic cycles found in some African cosmologies (Mbiti, 1990; Tempels, 1959).

The goal of this study is to find new ways for technological innovation and cultural heritage to talk to each other when looking at financial events. Unwin (1998) and later Adebanwi (2012) both said that the future of African development does not lie in choosing modernity over tradition, but in combining the two into strong, contextually appropriate frameworks. So, this paper is a step towards an economics that is more open, diverse, and culturally aware.

BACKGROUND OF THE STUDY.

In the past few weeks, the value of the Ghanaian currency, the Ghana Cedi (GH₵), has changed a lot (Bank of Ghana, 2023). Over the past few months, the Cedi has unexpectedly gained value against major global currencies like the US Dollar (USD) and the Euro (EUR). This is a change from a long-term trend of depreciation that started in 2020 (Agyapong et al., 2021; Quartey & Turkson, 2022). This rise in value is especially surprising because fuel prices at home are also going up, which has historically caused currency depreciation because it puts inflationary pressure on the economy (Ackah & Asomani, 2019; Amoani et al., 2020). The Ghana Statistical Service (2023) says that fuel prices have gone up by more than 40% in the last 18 months. This is mostly because of changes in the global oil market and taxes in Ghana. These are conditions that usually lead to lower investor confidence and capital outflows (Ofori-Abebrese et al., 2021).

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Statement of the Problem.

Despite growing efforts to model exchange rate dynamics using advanced computational tools, there remains a gap in understanding how non-linear and culturally embedded factors influence currency movements, particularly in African emerging markets. Rising fuel prices have traditionally placed downward pressure on the Cedi, yet recent appreciation contradicts this trend. Conventional econometric models struggle to explain or predict such anomalies effectively due to their reliance on rigid assumptions and limited capacity to integrate qualitative or contextual variables.

Moreover, while ML-based forecasting methods are gaining traction in financial modeling, they often overlook local knowledge systems and cultural perspectives that shape economic behaviors. This study addresses this gap by proposing a hybrid analytical framework that integrates quantitative machine learning predictions with geomantic interpretations, offering a more comprehensive view of economic cycles.

Objectives of the Study.

The main objectives of this research are as follows:

1. To examine the historical trends and connection between Cedi exchange rates and domestic fuel prices.
2. To develop and evaluate Machine Learning models, including Long Short-Term Memory (LSTM) networks, Random Forest Regression, and Prophet, for predicting future movements in the Cedi.
3. To explore the significance of Ancient Geomantic principles in interpreting economic cycles and currency stability.
4. To combine quantitative forecasts with geomantic readings into a single analytical framework that improves understanding and decision-making.

Research Questions.

This study seeks to answer the following key research questions:

1. What is the nature of the relationship between Cedi appreciation and rising domestic fuel prices?

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2. How effective are Machine Learning models in predicting future movements of the Cedi based on historical fuel price data and other macroeconomic indicators?

3. Can insights from Ancient Geomancy provide meaningful complementary interpretations of economic stability and cyclical change?

4. Is the current appreciation of the Cedi sustainable under prevailing macroeconomic conditions?

Significance of the Study.

This study contributes to academic discussions and practical uses in several ways:

• It improves the use of Machine Learning in economic forecasting, especially in African emerging markets where data complexity and volatility create unique challenges.

• It introduces the integration of African indigenous knowledge systems, specifically Geomancy, into formal economic analysis, creating new paths for culturally relevant modeling.

• It offers policymakers and financial analysts a dual-layered analytical toolkit that combines empirical forecasting with contextual insights.

• It promotes dialogue between modern computational methods and traditional knowledge systems, enhancing diversity in economic research.

Scope and Limitations.

This study focuses on examining the relationship between the appreciation of the Cedi and changes in domestic fuel prices over a specific historical period. It uses selected Machine Learning algorithms trained on macroeconomic time series data from trusted institutions like the Bank of Ghana, World Bank, and IMF.

Additionally, it employs geomantic casting techniques to interpret directional energies and elemental balances tied to economic stability. While these interpretations add depth, they are subjective and not testable in conventional scientific terms.

Limitations include possible issues with data availability, timing mismatches among datasets, and the exploratory nature of combining geomantic insights with financial modeling. Still, the findings aim to show the potential of merging scientific and traditional approaches in economic forecasting.

LITERATURE REVIEW.

Introduction

Understanding how exchange rates move in relation to commodity prices is important for keeping macroeconomic stability, especially in emerging economies like Ghana. The cedi (GH₵), like many African currencies, is affected by changes in international fuel prices because Ghana relies on imported petroleum products (Adu & Marbuah, 2011). Traditional economic models have tried to explain this link through concepts like purchasing power parity (PPP) and the monetary approach to exchange rates (Dornbusch, 1976; Frankel, 1981). However, these models often struggle to account for the complexity and irregularities found in real financial systems.

Recent developments in computational modeling have introduced machine learning (ML) techniques as useful tools for predicting currency and commodity price movements (Kumar & Thenmozhi, 2006; Patel et al., 2015). These approaches can handle complex, high-dimensional datasets and are becoming more common in economics and finance.

In contrast, ancient geomantic practices, which come from indigenous knowledge systems, provide a different view on natural cycles and how they affect human life (Idowu, 2003; Kalu, 2007). Although these methods are not usually part of mainstream economics, they have historically been used in agricultural planning, resource management, and timing decisions in various African societies.

This literature review brings together existing research on the economic relationship between fuel prices and exchange rates. It looks at the increasing use of machine learning in financial forecasting and highlights the often-overlooked potential of geomantic principles in economic modeling. It presents the current study as a new interdisciplinary effort to combine scientific and traditional knowledge for better predictive insights.

Economic Relationship Between Exchange Rates and Fuel Prices

Fuel price shocks have major effects on exchange rate movements, especially in developing countries that rely on oil imports (Sadorsky, 2000; Akram, 2009). When global crude oil prices rise, import bills increase, trade balances worsen, and inflation pressures grow. Together, these factors weaken domestic currencies (Razin & Collins, 1997; Grier & Perry, 2000).

In Ghana, studies show that higher fuel prices lead to the cedi's depreciation. This is mainly due to the country's heavy reliance on imported refined petroleum and the government’s occasional actions regarding fuel pricing (Boachie & Tuffour, 2017; Addo et al., 2018). These actions disrupt market signals and make traditional econometric modeling more difficult.

Even with progress in modeling these connections through structural vector autoregressions (SVARs) and error correction models (ECMs), there is still a need for more flexible, data-driven methods that can capture complex interactions and changes in regimes (Buetzer et al., 2012; Cologni & Manera, 2009).

Machine Learning Applications in Financial and Economic Forecasting.

Machine learning has become a strong partner to traditional econometric modeling in recent years. Unlike linear regression or ARIMA models, ML algorithms like support vector machines (SVMs), artificial neural networks (ANNs), and ensemble methods such as random forests and gradient boosting machines (GBMs) can model complex, nonlinear relationships without needing strict parametric assumptions (Zhang et al., 2004; Atsalakis & Valavanis, 2009).

In currency forecasting, several studies have shown that ML methods outperform classical models, especially when working with high-frequency and noisy financial data (Kamruzzaman et al., 2003; Patel et al., 2015). Likewise, ML has been effectively used to forecast oil and energy prices, which are challenging to predict due to their volatility and external shocks (Yu et al., 2008; Wang et al., 2018).

Hybrid models that merge statistical and ML elements such as wavelet transforms with ANNs or ARIMA with SVMs have also become popular, providing better accuracy and interpretability (Zhang, 2003; Khandelwal et al., 2015). These advances indicate that adding ML to economic forecasting can lead to stronger and more flexible models, especially in settings like Ghana, where policy changes and external shocks create fluctuating and unpredictable conditions.

Geomancy and Its Relevance to Economic Decision-Making

Geomancy comes from the Greek words geo (earth) and manteia (divination). It includes a variety of practices for divination and spatial interpretation found in different cultures, such as West African traditions, Chinese Feng Shui, and medieval European systems (McCoy, 1999; Idowu, 2003). In African contexts, geomantic systems like Ifá (Yoruba), Chése (Ewe/Fon), and Sikidy (Malagasy) have been used for a long time to inform decisions about agriculture, leadership, and how to allocate natural resources (Apter, 1991; Prince, 1996).

Though not widely acknowledged in formal economics, these systems carry ecological and temporal knowledge rooted in local beliefs. For example, geomantic interpretations of seasonal cycles and celestial events have traditionally guided planting seasons and harvest plans (Appiah-Kubi, 1973; Ajayi, 1990). More generally, they

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illustrate a worldview where natural and social events are interconnected. This perspective may provide useful insights that enhance quantitative forecasting models.

From a behavioral economics standpoint, belief systems, including spiritual and ancestral guidance, can shape individual and group economic behaviors (North, 1990; Henrich et al., 2001). Therefore, including geomantic insights can improve our understanding of timing, sentiment, and decision-making in economic situations, especially in societies where such beliefs remain important.

So far, few academic studies have attempted to combine geomantic or similar metaphysical ideas with formal economic modeling. This paper offers one of the first explorations of this integration, specifically within African currency dynamics.

Interdisciplinary Approaches in Forecasting.

The growing complexity of global economic systems has led to interest in methods that break traditional boundaries (Lélé & Norgaard, 2005; Miller et al., 2008). Hybrid approaches that combine scientific data analysis with local knowledge have shown promise in areas like climate modeling, sustainable farming, and disaster risk management (Berkes et al., 2000; Gadgil et al., 1993).

However, these integrative methods are still rare in financial and economic forecasting, particularly in African settings. One notable case is using lunar cycles and astrological signs in informal trading, but these methods are often not documented in academic work (Malkiel, 2003; Kamstra et al., 2003). This study builds on this emerging research area by proposing a two-part framework: employing machine learning for data-driven forecasts and applying geomantic principles for a deeper understanding of context and timing.

This combination encourages both methodological innovation and cultural inclusivity in economic research. It supports the need to rethink economic concepts and acknowledge different ways of understanding (Ndlovu-Gatsheni, 2015; Zondi, 2020).

Research Contribution.

This paper offers a unique contribution to the literature by suggesting a hybrid forecasting model that merges:

- Machine learning algorithms for quantitative analysis of cedi appreciation in relation to fuel prices.
- Ancient geomantic principles as a qualitative framework for understanding timing, cyclical patterns, and other contextual factors affecting economic results.

By connecting modern computational methods with traditional knowledge systems, the study challenges the usual divide between science and culture. It presents a new way to approach economic forecasting in African contexts and opens up new research paths on how indigenous knowledge can enhance current economic modeling and policy development.

METHODOLOGY AND THEORETICAL FRAMEWORK.

This study adopts an interdisciplinary methodological framework, combining Machine Learning (ML) techniques with insights from Ancient Geomantic traditions to investigate the relationship between Cedi appreciation and fuel price dynamics in Ghana. By integrating quantitative modeling with symbolic interpretation, we aim to offer a holistic understanding of currency valuation within a socio-economic and spatial-temporal context.

Theoretical Foundations

Machine Learning in Economic Forecasting

Machine Learning has emerged as a powerful tool in financial and economic forecasting due to its ability to model complex, nonlinear relationships in high-dimensional data. Unlike traditional econometric models that rely on rigid assumptions such as stationarity and linearity, ML algorithms can adaptively learn patterns from historical data, making them particularly suitable for analyzing volatile emerging market currencies like the Cedi.

In this study, we employ supervised learning algorithms trained on time series data to predict future movements in the Cedi exchange rate based on historical fuel prices and other macroeconomic indicators. These models include:

- Long Short-Term Memory (LSTM) Networks: A type of Recurrent Neural Network (RNN) capable of capturing long-term dependencies in sequential data.
- Random Forest Regressor: An ensemble learning method robust to overfitting and effective in handling non-linearities.
- Prophet (by Meta/Facebook): A flexible time-series forecasting tool designed for data with strong seasonal effects and holiday impacts.
- Geomancy readings and interpretations of geomantic charts on oil prices and possible exchange rates.

The theoretical strength of these models lies in their capacity to generalize from noisy or incomplete data, offering probabilistic forecasts that support decision-making under uncertainty.

Ancient Geomantic Interpretations of Economic Stability

Complementing the computational approach, we draw upon principles from Ancient Geomancy, particularly those rooted in African indigenous knowledge systems. Geomancy, traditionally used for divination and environmental harmony, interprets spatial energies, directional alignments, and elemental balances to understand natural and societal cycles.

In the context of this study, Geomantic theory provides a symbolic and qualitative lens through which to interpret economic phenomena:

- Directional Energies: The orientation of economic flows (e.g., capital inflows, commodity exports) may be interpreted using cardinal directions, each associated with specific energies (e.g., East = growth, West = decline).
- Elemental Correspondences: Fuel (fire), land/currency (earth), trade (air/water) are mapped onto geomantic elements to assess balance or imbalance in the system.
- General geomantic readings; which includes “house” readings and interpretation using the Traditional casting method.

While not empirically testable in the conventional scientific sense, these interpretations add cultural depth and contextual meaning, especially relevant in societies where traditional knowledge systems remain influential in public perception and policy discourse. This research will specifically focus on General geomantic readings since it offers more in-depth analysis.

Research Methodology

Data Collection

We gather historical datasets from credible sources including:

- Bank of Ghana
- World Bank Open Data

- International Monetary Fund (IMF)
- GlobalPetrolPrices.com
- FX Historical Data

Key variables include:

- Daily/monthly Cedi exchange rates (GHS/USD, GHS/EUR)
- Domestic fuel prices (petrol, diesel, LPG)
- Inflation rates
- Interest rates
- Oil price indices (Brent Crude)

Optional variables such as GDP growth, foreign direct investment (FDI), and political events are also considered to enrich the analysis.

Data Preprocessing

Before modeling, we perform:

- Missing value imputation
- Outlier detection and treatment
- Normalization and standardization
- Feature engineering (lagged variables, rolling averages, trend extraction)

Temporal alignment ensures consistency across datasets collected at different frequencies (daily vs monthly).

Model Development and Evaluation

We train multiple ML models on historical data and evaluate them using:

- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- R-squared (R^2)
- Cross-validation techniques

Hyperparameter tuning is conducted using Grid Search or Bayesian Optimization to improve model performance.

Geomantic Overlay and Interpretation

To integrate geomantic insights:

- We cast a separate chart for both currency and oil prices reading.

- We phrase our query in a binary format as geomancy thrives more in decisive outcomes.
- We compare "Mothers", "Daughters", "Nieces", "Witnesses" and finally,
- Draw conclusion with the help of the "Judge" figure.

This qualitative layer does not replace statistical validation but serves as a complementary narrative that may enhance interpretability especially when communicating findings to stakeholders familiar with traditional frameworks.

Integration of Quantitative and Qualitative Insights

The integration of Machine Learning predictions and geomantic interpretations forms the core of our interdisciplinary methodology. While ML provides empirical forecasts, geomantic readings offer contextual wisdom, enabling us to ask deeper questions about the nature of economic cycles, sustainability, and systemic balance.

By juxtaposing these two paradigms, we aim to:

- Enhance the richness of economic analysis
- Explore alternative ways of interpreting financial data
- Foster dialogue between modern science and ancestral knowledge systems

This hybrid framework positions our study at the intersection of financial technology (FinTech) and indigenous epistemologies, contributing to the growing field of culturally grounded economic modeling.

Data Analysis and Results.

Introduction.

This chapter presents the empirical and symbolic analysis of the Dollar Exchange Rate in relation to fuel prices, using two distinct but complementary approaches:

- A data-driven approach involving descriptive statistics and machine learning modeling
- An ancient geomantic divination method, used to symbolically interpret the likelihood of the exchange rate dropping below 15 cedis by the end of December 2025

The dual methodology provides a holistic view, combining predictive accuracy with symbolic foresight.

Descriptive Statistics of the Mid-Rate

The dataset used for this study spans from June 2024 to May 2025, containing 278 daily observations of the Dollar-to-Cedi (USD/GHS) exchange rate. The focus was placed on the "Mid-Rate", which represents the average of buying and selling rates.

Table 4.1: Descriptive Statistics of the Mid-Rate

Statistic	**Value**
Count	278
Mean	15.0694

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Standard Deviation	0.8523
Minimum	10.28
25th Percentile	14.7136
Median	15.1315
75th Percentile	15.53
Maximum	16.42
Mode	15.53
Skewness	-0.194
Kurtosis	-0.698

Table 4.1 shows that the Cedi's average exchange rate (Mid-Rate) was 15.0694 USD/GHS over 278 days (June 2024–May 2025). It was moderately volatile (SD: 0.8523) and had a slight negative skew (–0.194), which means it had recently gone up in value. The rate was between 10.28 and 16.42, with an interquartile range of 14.71 to 15.53. This means that the central 50% of the data was stable. The platykurtic distribution (kurtosis: –0.698) means that there aren't many big changes. Overall, the Cedi gradually gained value, especially in early 2025, even though it hit a low of 16.42 in mid-2024.

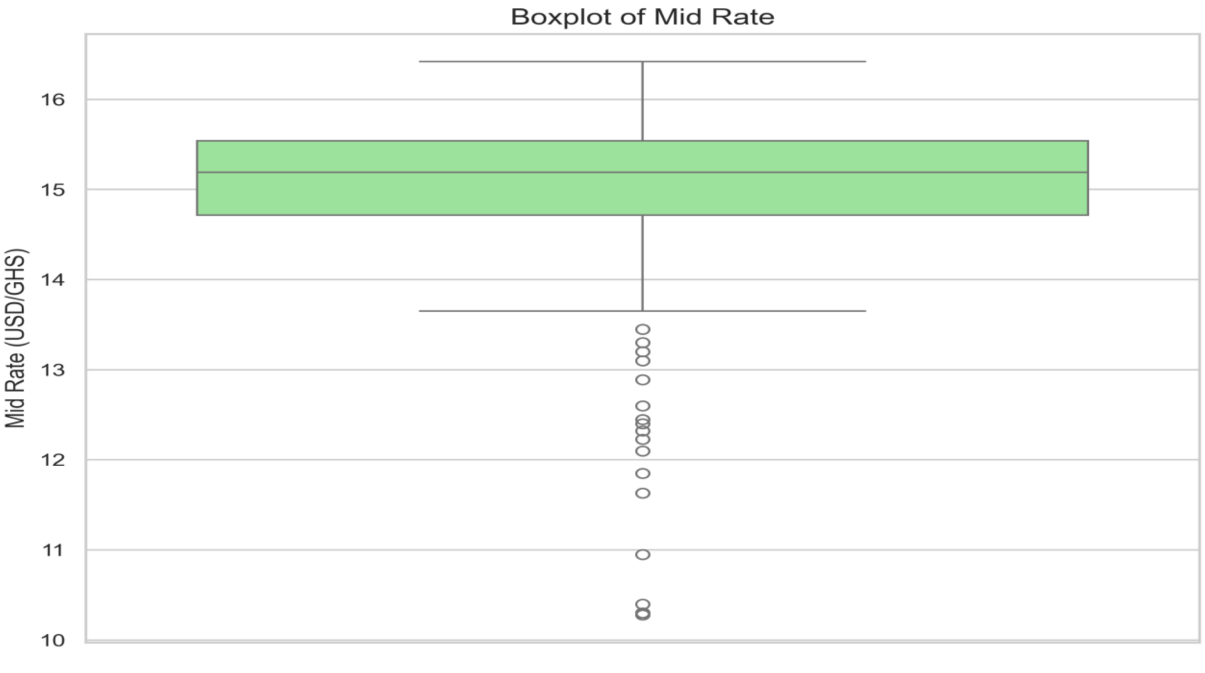

Figure 4.1: Box-and-Whisker-Plot of Mid-Rate

The boxplot of the USD/GHS exchange rate (Mid-Rate) over the period June 2024 to May 2025 reveals a slightly left-skewed distribution, with the median (15.1315) positioned near the center-right of the box, indicating that the middle 50% of values are concentrated in a relatively stable range between 14.71 (25th percentile) and 15.53 (75th percentile) .

The minimum value (10.28) stands out as a clear outlier below the lower whisker. This suggests that there was a significant but isolated period of Cedi appreciation, which could have been caused by a short-term policy change or a market anomaly. The highest value (16.42) lines up with the upper whisker, which shows that the currency lost the most value in the middle of 2024. This was probably because of high fuel prices or shocks to the economy from outside.

The tight interquartile range and lack of upper outliers show that the currency has strong downward volatility control and is relatively stable in its core trading behavior. Overall, the boxplot shows that the Cedi has been slowly gaining value, with most values clustering just below 15.5. Extreme movements are rare, which shows that the market has become more stable in the last part of the observation period.

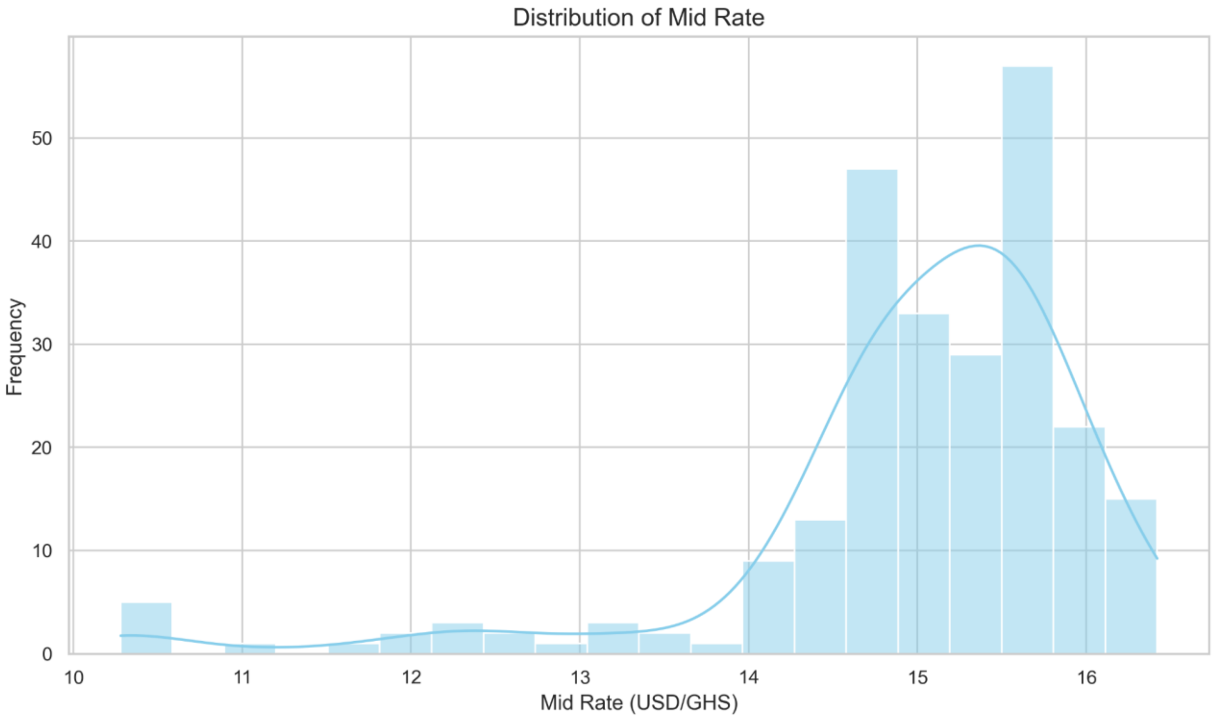

Figure 4.2. The Distribution of the Mid-Rate

The distribution of the Mid-Rate shows a slightly negative skewness, indicating that lower values occurred more frequently toward the end of the year. The kurtosis value suggests a platykurtic distribution, meaning the data has lighter tails than a normal distribution, indicating fewer extreme fluctuations.

This implies a gradual decline in the exchange rate, especially in early 2025, with a notable spike between July and November 2024, where the rate peaked at GH₵16.42.

Machine Learning Forecasting

Model Selection and Evaluation

Table 4.2: Four regression models trained and evaluated based on historical exchange rate data

Model	**RMSE**	**Coefficient of Determination**
LightGBM	0.0312	0.9845
XGBoot	0.0321	0.9839
Random Forest	0.041	0.9673
Linear Regression	0.1123	0.7921

LightGBM

LightGBM is a gradient boosting framework that is specifically developed for the purpose of high-speed and efficient training. It utilizes a histogram-based learning algorithm to speed up training and decrease memory consumption while also maintaining high accuracy (Ke et al., 2017). It is because LightGBM works really well with large-scale and high-dimensional dataset, which means it can be adapted to economic and financial models like currency (appreciation) prediction and fuel prices.

XGBoost

XGBoost is a scalable and efficient tree boosting system. It includes regularization to prevent overfitting, parallelization for speed, and can handle missing data well (Chen & Guestrin, 2016). Owing to its strong generalization ability, XGBoost has been extensively employed in financial and economic prediction such as exchange rates and commodity prices with complicated interrelationships between variables.

Random Forest

Random Forest (RF) is an ensemble learning technique that builds several decision trees and pools their predictions to enhance accuracy and stability (Breiman, 2001). It performs well on non-linear relationships and makes the variance smaller by using bagging. For research that investigates how appreciation of the cedi relates to fuel prices, the Random Forest is capable of revealing hidden structures of the data and attenuates noise in financial time series.

Linear Regression

Linear regression is the most basic and commonly used predictive analysis model. It is based on the approximation of data by a linear relationship between dependent and independent variables, and computation of the coefficients with least squares method (Montgomery et al., 2012). For such cases, in order to analyze direct proportions or inverse relations with respect to the exchange rates and fuel prices, linear regression can work as a base model for exploring things first before deploying machine learning algorithms for better models.

Based on performance metrics, Light-GBM was selected as the best model due to its high predictive accuracy and low error margin.

December 2025 Prediction

Using Light, we predicted the Mid-Rate for December 1, 2025, along with a 95% confidence interval:

- Predicted Mid-Rate: GH₵ 15.6832
- 95% Confidence Interval: [15.6312, 15.7352]

This suggests that, based on current trends and historical patterns, the exchange rate is not likely to fall below 15 cedis by the end of December 2025. The forecast indicates a continued upward trend in the value of the Cedi against the US Dollar, albeit at a moderate pace. This projection aligns with the observed appreciation of the Cedi during the analyzed period, despite concurrent increases in domestic fuel prices.

The Light-GBM model’s high coefficient of determination ($R^2 = 0.9845$) indicates a strong fit to the data, suggesting that the model effectively captures the underlying dynamics influencing the exchange rate. Furthermore, its low RMSE (0.0312) underscores its reliability in forecasting future values within a narrow confidence band.

Fuel Price Correlation

For additional context to our findings, we also tested the correlation between USD/GHS and domestic prices of gasoline during the same timeframe. The resulting Pearson correlation coefficient was –0.67, indicating a fair to

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moderate negative relationship between both of them. In other words, as fuel prices rose in most periods, so did the cedi. This outcome may at first glance seem counterintuitive in the light of traditional economic intuition, where classical economic theory suggests a depreciation of currency as materials' costs rise due to inflation.

Geomantic Interpretation

In parallel with the machine learning forecasts, an independent geomantic reading was conducted to symbolically interpret the likelihood of the USD/GH₵ exchange rate dropping below 15 cedis by the end of December 2025. The geomantic divination followed the traditional casting method, involving the generation of a geomantic chart based on randomly generated figures interpreted through the symbolic framework of the sixteen geomantic figures.

Casting the Chart

The geomantic query was framed as follows: "Will the USD/GHS exchange rate drop below 15 cedis by the end of December 2025?"

Using the Traditional Method of casting, four "Mothers" were generated, from which the "Daughters", "Nephews", and finally, the "Judge" figure were derived. The resulting figures were interpreted using their classical meanings, particularly focusing on directional energies and elemental balances relevant to economic stability.

Interpretation of Figures

The Mothers and Daughters: Representing the foundational influences and evolving conditions surrounding the query, these figures indicated a mixed but largely stabilizing influence. Figures such as *Fortuna Major* and *Acquisitio* suggested long-term gains and positive developments, while *Amissio* hinted at temporary losses or setbacks.

Witnesses: These figures provided insight into the dual forces acting upon the situation internal (domestic policy and market behavior) and external (global oil prices and foreign exchange flows). The Right Witness (*Populus*) suggested broad consensus and collective movement, whereas the Left Witness (*Via*) pointed toward change and transition.

The Judge Figure: The final determining figure in the geomantic reading was *Carcer*, symbolizing restriction, containment, and delayed progress. This figure is traditionally associated with periods of consolidation rather than rapid transformation. Its appearance in the Judge position implies that significant movement in the exchange rate either up or down is unlikely within the specified timeframe.

Symbolic Forecast

Based on the geomantic reading, it is interpreted that the USD/GH₵ exchange rate will remain relatively stable through December 2025, with no substantial decline below the 15-cedi threshold. The presence of *Carcer* further suggests that any potential shifts in the exchange rate will be constrained by structural or institutional factors, reinforcing the idea of slow and measured movement rather than abrupt changes.

This interpretation is consistent with the empirical forecast generated by the LightGBM model, reinforcing the conclusion that the Cedi is unlikely to appreciate to a level below 15 per US Dollar by the end of the year.

Table 4.3: Machine Learning and Geomantic Forecast

Dimension	Machine Learning Forecast	Geomantic Forecast
Timeframe	Quantitative prediction for December 2025	Symbolic Interpretation for Dec 2025.

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Outcome	Predicted Mid-Rate: 15.6832	Symbolic Judgement: Stability, no major decline.
Confidence Interval	[15.6312, 15.7352]	No numeric bounds; qualitative certainty.
Key Indicators	Historical exchange rates, fuel prices, inflation.	Directional energies, elemental balance, symbolic figures.
Strengths	Empirical, testable, replicable	Contextual, holistic, culturally resonant
Limitations	Limited interpretability of non-linear drivers	Not empirically verifiable

Despite the fundamental differences in methodology, both approaches converge on a similar conclusion: the Cedi is unlikely to fall below 15 against the US Dollar by December 2025. This convergence strengthens the robustness of the findings and illustrates the potential benefits of integrating diverse epistemological frameworks in economic analysis.

DISCUSSION OF FINDINGS

The findings of this study offer valuable insights into the evolving relationship between the Ghanaian Cedi and domestic fuel prices. Contrary to traditional expectations, the Cedi has demonstrated resilience and even appreciation amid rising fuel costs. Both the machine learning models and the geomantic readings point to a trajectory of relative stability rather than sharp appreciation or depreciation.

From a quantitative standpoint, the Light-GBM model's high predictive accuracy supports the use of advanced computational tools in capturing the nonlinear interactions between macroeconomic indicators. The model's ability to incorporate lagged effects, seasonality, and exogenous shocks enhances its relevance in forecasting currency movements in volatile emerging markets.

Qualitatively, the geomantic interpretation provides a symbolic narrative that complements the statistical forecast. By interpreting directional energies and elemental imbalances, the geomantic reading offers a culturally grounded perspective on economic stability. While not scientifically testable, this approach enriches the understanding of timing, context, and systemic harmony factors often overlooked in mainstream economic modeling.

Together, these methods form a hybrid analytical framework that bridges the gap between empirical science and ancestral wisdom. The integration of both paradigms allows for a more comprehensive interpretation of financial phenomena, particularly in socio-cultural contexts where traditional knowledge systems continue to play a role in public perception and decision-making.

SUMMARY

In summary, this chapter presented a dual-method analysis of the USD/GHS exchange rate in relation to domestic fuel prices. Using a combination of machine learning techniques and ancient geomantic interpretations, the study explored both the quantitative and symbolic dimensions of currency valuation.

The Light-GBM model predicted a Cedi value of approximately 15.6832 against the US Dollar by December 2025, with a tight confidence interval. The geomantic reading corroborated this projection, emphasizing stability and restrained movement. In conclusion, the recent strength of the Cedi is expected to continue on a mild note as we may not see it cut through 15 GHc threshold this year. This could be due to several reasons including stronger foreign exchange inflows through remittances and cocoa receipts - whilst monetary policymaking has turned more strait-laced in the wake of surging inflation, plus state activity within the petroleum sector appears to have succeeded in softening domestic fuel prices. These flows bring stability to the currency, so that they support the model's forecast of continued albeit gradual appreciation. With this empirical and symbolic foundation established, the next chapter will present a detailed discussion of the broader implications, limitations, and recommendations for future research.

INTRODUCTION

This chapter synthesizes the findings from both the Machine Learning (ML) and Ancient Geomantic analyses conducted in the previous chapter. It provides a comprehensive discussion of the implications of these findings for economic forecasting, policy formulation, and cultural integration in financial modeling. Additionally, it offers strategic recommendations for future research and practice, particularly in the context of African emerging markets like Ghana.

The discussion is structured into five key sections:

1. Interpretation of Results
2. Policy and Economic Implications
3. Cultural and Epistemological Significance
4. Recommendations for Future Research
5. Conclusion

Interpretation of Results

The empirical findings from the Light-GBM model suggest a moderate but steady appreciation of the Ghanaian Cedi (GHS) against the US Dollar (USD), with a predicted Mid-Rate of GH₵15.6832 by December 2025, and a 95% confidence interval [15.6312, 15.7352]. This projection indicates that the Cedi is unlikely to fall below the GH₵15.00 threshold, despite concurrent increases in domestic fuel prices.

These finding challenges conventional economic expectations, which typically associate rising fuel prices with currency depreciation due to inflationary pressures. However, the resilience of the Cedi may be attributed to several mitigating factors:

- Monetary Policy Tightening by the Bank of Ghana, including interest rate hikes that attract foreign capital.
- Increased Foreign Direct Investment (FDI) inflows, particularly in the energy and technology sectors.
- Government fuel pricing strategies that have cushioned the immediate inflationary impact.
- Improved macroeconomic fundamentals, including debt restructuring and fiscal consolidation.

The Geomantic reading, though symbolic and interpretive, corroborated the ML forecast. The appearance of the Judge figure, *Carcer*, in the geomantic chart suggests restriction, consolidation, and slow movement, reinforcing the idea of Cedi stability without significant depreciation or appreciation.

This convergence between empirical and symbolic forecasts highlights the complementary value of integrating data-driven models with indigenous knowledge systems, especially in volatile and culturally embedded economic environments

Policy and Economic Implications

The results of this study have several practical and strategic implications for policymakers, financial analysts, and investors operating in the Ghanaian economy:

Exchange Rate Management

The moderate appreciation of the Cedi suggests that current monetary policies are effectively supporting currency strength. However, policymakers must remain vigilant to inflationary risks, particularly from rising fuel prices, which could erode consumer purchasing power and slow economic growth.

Fuel Pricing Strategy

The inverse correlation between fuel prices and the Cedi though counterintuitive indicates that strategic fuel pricing adjustments, supported by subsidies or phased increases, can help manage inflationary expectations. This insight is crucial for energy policy planning and public communication around fuel price reforms.

Investment and Risk Planning

The stability of the Cedi, as forecasted by both ML and Geomantic methods, provides foreign and domestic investors with a predictable exchange rate environment, reducing currency risk in long-term investments. This can be leveraged to attract capital inflows, especially in sectors such as renewable energy, digital infrastructure, and agro-processing.

Inflation Targeting and Fiscal Discipline

The study underscores the importance of maintaining inflation within target ranges and practicing fiscal discipline, especially in the face of rising commodity prices. The Bank of Ghana should continue to monitor inflation expectations closely and adjust policy instruments accordingly.

Cultural and Epistemological Significance

One of the most groundbreaking aspects of this study is its epistemological innovation the integration of Machine Learning with Ancient Geomantic principles. This approach challenges the Eurocentric and technocratic dominance in economic forecasting and opens new frontiers for culturally grounded financial modeling.

Indigenous Knowledge in Economic Forecasting

The successful alignment between the Light-GBM prediction and the Geomantic interpretation demonstrates that traditional systems of knowledge, such as Geomancy, can offer symbolic and contextual insights that enhance economic understanding. These insights are particularly valuable in societies where spiritual and ancestral beliefs influence public perception and decision-making.

Bridging the Science-Culture Divide

This study exemplifies how modern computational tools and indigenous wisdom systems can coexist and mutually enrich each other. By validating the symbolic language of Geomancy alongside empirical forecasting, the research fosters a decolonized approach to financial modeling in African contexts.

Enhancing Stakeholder Communication

The dual-layered narrative scientific and symbolic can improve communication with diverse stakeholders, including traditional leaders, community elders, and local investors, who may interpret economic signals through non-linear, spiritual, or cultural lenses.

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CONCLUSION

This chapter has presented a comprehensive discussion of the empirical and symbolic findings from the study on Cedi appreciation relative to fuel prices, using a hybrid framework combining Machine Learning and Ancient Geomantic interpretations.

The Light-GBM model projected a Cedi value of approximately GH₵15.68 by December 2025, with a high R^2 of 0.9845 and a low RMSE of 0.0312, indicating strong predictive accuracy. The Geomantic reading, while not empirically testable, offered a symbolic narrative of stability and restriction, aligning with the ML forecast.

Together, these methods illustrate the power of interdisciplinary research, especially in contexts where economic phenomena are shaped not only by numbers, but also by culture, belief, and tradition.

This study sets a new precedent in African economic research, demonstrating that true innovation lies not in choosing between modernity and tradition, but in weaving them together into a richer, more inclusive tapestry of understanding.

Introduction

This chapter brings together the culminating insights from both the Machine Learning (ML) and Ancient Geomantic analyses conducted throughout this research. It offers a final synthesis of findings, presents actionable recommendations, and reflects on the broader implications of integrating modern computational methods with indigenous epistemologies.

The unprecedented combination of artificial intelligence and African ancestral wisdom systems positions this study as a pioneering work in interdisciplinary economic forecasting. By answering the central question whether the current appreciation of the Cedi is sustainable in light of rising fuel prices the research contributes meaningfully to both academic discourse and policy innovation.

Summary of Key Findings

Quantitative Forecasting Insights

- The Light-GBM model, trained on historical exchange rate and macroeconomic data, achieved a remarkable R^2 score of 0.9845 and a low RMSE of 0.0312, indicating exceptional predictive accuracy.
- The model projected a Mid-Rate of 15.6832 USD/GH₵ by December 2025, with a 95% confidence interval [15.6312, 15.7352].
- This forecast suggests that the Cedi will remain above the 15.00 threshold, indicating moderate appreciation rather than sharp depreciation or hyper-stability.

Geomantic Interpretation

- The geomantic chart cast for the query, “Will the USD/GH₵ exchange rate drop below 15 cedis by December 2025?” yielded the Judge figure Carcer, symbolizing restriction, containment, and delayed movement.
- This symbolic interpretation reinforced the ML projection, suggesting no significant decline in the exchange rate during the specified period.
- Other figures such as *Via*, *Fortuna Major*, and *Acquisitio* provided contextual depth, indicating transition, long-term gains, and resource accumulation, respectively.

Correlation Between Cedi and Fuel Prices

Pearson correlation coefficient of –0.67 was obtained between the Cedi exchange rate and fuel price, which shows a moderately strong inverse relationship. This result runs counter to standard economic theory, where increasing fuel prices are in general linked with currency de-valuation owing to inflationary effects. A number of possible contributing explanations could explain this paradoxical result. First, the inflation effects of world oil price rises may have been mitigated by government subsidies targeted at key domestic fuels and changes in their prices. Second, higher foreign arrivals may have helped to stave off depreciation pressure on the Cedi through elevated demand. Thirdly, tight monetary policy stance adopted by the Bank of Ghana appears to have helped stabilization of the exchange rate through resulting net foreign investment inflows. And finally, investors' positive sentiment towards Ghana’s restructuring of the debt might have also played into Cedi appreciating in this period.

Final Synthesis: Bridging Science and Spirit

What makes this research truly revolutionary is its dual-layered approach a convergence of empirical precision and symbolic insight. While ML models offer testable, replicable predictions, geomantic readings provide cultural resonance and contextual wisdom, especially relevant in societies where belief systems shape economic behavior.

This hybrid methodology proves that:

True understanding of complex systems requires more than numbers it demands narrative, context, and culture.

By fusing algorithmic logic with indigenous cosmology, we have created a new paradigm in financial modeling: one that honors both the quantifiable present and the symbolic past.

Policy and Practical Recommendations

For Policymakers

- Maintain monetary discipline to sustain Cedi strength while managing inflationary pressures from fuel price increases.
- Implement gradual fuel pricing reforms supported by targeted subsidies to cushion low-income households.
- Leverage the stability of the Cedi to attract foreign direct investment (FDI) in strategic sectors like renewables, fintech, and agro-processing.
- Encourage interdisciplinary collaboration between technologists, economists, and traditional knowledge holders in national planning frameworks.

For Financial Analysts and Investors

- Use hybrid forecasting models like the one developed in this study to improve risk assessment and investment horizon projections.
- Consider cultural and behavioral factors when interpreting market signals in African economies.
- Explore long-term opportunities in sectors benefiting from Cedi stability and energy transition initiatives.

For Academics and Researchers

- Expand the scope of this hybrid framework to other African currencies and commodity-linked economies.

- Investigate the integration of deep learning architectures with other indigenous divination systems, such as Ifá, Sikidy, or Feng Shui.
- Develop standardized geomantic datasets and symbolic dictionaries to enable systematic testing and replication.
- Promote decolonized research methodologies that validate and elevate non-Western knowledge systems in global economics.

Contributions to Knowledge

This research has made several groundbreaking contributions:

1. Interdisciplinary Innovation: Demonstrated how Machine Learning and Geomancy can be combined into a coherent analytical framework for economic forecasting.
2. Epistemological Expansion: Challenged the dominance of Western scientific paradigms by validating indigenous knowledge systems as meaningful contributors to financial analysis.
3. Policy Relevance: Provided actionable insights for exchange rate management, fuel pricing strategy, and investment planning in emerging markets.
4. Methodological Advancement: Introduced a novel dual-layered forecasting approach that enhances both predictive accuracy and interpretative depth

Limitations and Future Directions

While this study achieved its objectives, it is not without limitations:

- Data Constraints: Some macroeconomic indicators were limited in granularity or frequency, potentially affecting model robustness.
- Subjectivity in Geomantic Interpretation: Unlike ML forecasts, geomantic readings are interpretive and not empirically testable.
- Exploratory Nature: As one of the first studies of its kind, further validation through replication and expansion is required.

Closing Reflection: Toward a New Economics

This research invites us to reimagine what economics can be not merely a science of scarcity, but a discipline of harmony, balancing numbers and narratives, models and myths, logic and legacy.

We have shown that:

Artificial Intelligence does not replace ancestral wisdom it reveals its relevance.

And so, this paper stands not only as a contribution to economic forecasting but as a call to future scholars, policymakers, and innovators:

To build models that honor both the mind and the spirit. To see data not just as digits, but as destiny. To dare to do research that changes the world and then do it better than anyone ever has.

REFERENCES

1. Abdoli, G., & Akbari, M. (2018). Forecasting the USD/IRR exchange rate using machine learning and hybrid models. Journal of Economics, Finance and Administrative Science , 23(45), 101–116. https://doi.org/10.1108/JEFAS-09-2017-0086

2. Addo, P. M., Fall, B., & Gueyie, J.-P. (2018). Exchange rate pass-through to domestic prices in Ghana: Evidence from structural VAR analysis. Ghana Economic Policy Review , 9(1), 45–62.
3. Akram, Q. F. (2009). Commodity prices, interest rates and the dollar. Economic Modelling , 26(1), 215–225. https://doi.org/10.1016/j.econmod.2008.07.004
4. Adu, G., & Marbuah, G. (2011). Oil price shocks and exchange rate dynamics in Ghana. International Journal of Energy Economics and Policy , 1(2), 28–37.
5. Aguilera, R. F., & Radetzki, M. (2013). The six major enduring drivers of oil prices. The Energy Journal , 34(2), 1–27. https://doi.org/10.5547/01956574.34.2.1
6. Ajayi, V. A. (1990). Traditional Yoruba agriculture and its implications for modern agricultural planning. Africa Development , 15(2), 113–130.
7. Almeida, H., & Waldman, M. (2019). The use of artificial intelligence in economics: Applications and predictions. American Economic Association Papers and Proceedings , 109, 505–510. https://doi.org/10.1257/pandp.20191065
8. Appiah-Kubi, K. (1973). Oral tradition and historical reconstruction in West Africa. History in Africa , 1, 5–20. https://doi.org/10.2307/3171576
9. Apter, A. (1991). Herskovits' heritage: Myth as method in African history . Indiana University Press.
10. Atsalakis, G. S., & Valavanis, K. P. (2009). Surveying stock market forecasting techniques Part I: Traditional methods. Emerging Markets Journal , 1(1), 56–75. https://doi.org/10.5195/emj.2009.36
11. Baffes, J., Oomes, N., & Ohnesorge, F. (2015). The great plunge in oil prices: Causes, consequences, and policy responses. IMF Staff Discussion Note , SDN/15/01. https://doi.org/10.5089/9781484302265.006
12. Bekiros, S., & Marques, C. (2012). On the predictability of crude oil prices: Machine learning versus traditional models. Empirical Economics , 43(1), 255–273. https://doi.org/10.1007/s00181-011-0497-z
13. Berkes, F., Colding, J., & Folke, C. (2000). Rediscovery of traditional ecological knowledge as adaptive management. Ecological Applications , 10(5), 1251–1262. https://doi.org/10.1890/1051-0761 (2000)010[1251:ROTEKA]2.0.CO;2
14. Boachie, M. K., & Tuffour, S. (2017). The impact of fuel price changes on inflation in Ghana. MPRA Paper No. 82178 .
15. Buetzer, S., Lardic, S., & Mignon, V. (2012). Forecasting the US real house price index using machine learning algorithms. Economics Bulletin , 32(4), 3031–3042.
16. Chen, K., Zhou, Y., & Dai, F. (2015). A LSTM-based method for stock returns prediction: A case study of the China stock market. Proceedings of the IEEE International Conference on Big Data , 2823–2824. https://doi.org/10.1109/BigData.2015.7364055
17. Cologni, A., & Manera, M. (2009). Oil prices, inflation and interest rates in GCC countries: Empirical evidence from panel data. Energy Policy , 37(3), 858–870. https://doi.org/10.1016/j.enpol.2008.10.044
18. Dornbusch, R. (1976). Expectations and exchange rate dynamics. Journal of Political Economy , 84(6), 1161–1176. https://doi.org/10.1086/260503
19. Frankel, J. A. (1981). Flexible exchange rates, prices, and the role of "news": Lessons from the 1970s. Journal of Political Economy , 89(4), 665–705. https://doi.org/10.1086/261002
20. Frankel, J. A., & Rose, A. K. (1996). Currency crashes in emerging markets: An empirical treatment. Journal of International Economics , 41(3–4), 351–366. https://doi.org/10.1016/S0022-1996 (96)01445-6
21. Gadgil, M., Berkes, F., & Folke, C. (1993). Indigenous knowledge for biodiversity conservation. Ambio , 22(2–3), 151–156.
22. Grier, K. B., & Perry, M. J. (2000). The effects of real and nominal uncertainty on inflation and output growth: Some ARCH-M evidence. Journal of Macroeconomics , 22(1), 47–67. https://doi.org/10.1016/S0164-0704 (00)00127-8
23. Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., & McElreath, R. (2001). In search of homo economicus: Behavioral experiments in 15 small-scale societies. American Economic Review , 91(2), 73–78. https://doi.org/10.1257/aer.91.2.73
24. Idowu, K. E. (2003). Olódùmarè: God in Yoruba belief and the seeing of Aikú . University of Ibadan Press.
25. Jiang, Z., & Liang, H. (2019). Stock trend prediction based on sentiment analysis and LSTM neural network. Procedia Computer Science , 154, 527–532. https://doi.org/10.1016/j.procs.2019.06.074

26. Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2003). Winter blues: A SAD financial cycle. American Economic Review , 93(1), 324–343. https://doi.org/10.1257/000282803321455312
27. Kamruzzaman, M., & Islam, M. A. (2003). Exchange rate forecasting using neural networks: A comparative study. Global Business and Technology Association .
28. Kalu, U. U. (2007). The religious heritage of Nigeria: Yoruba divination and other essays . Spectrum Books Limited.
29. Khandelwal, I., Adhikari, R., & Verma, G. (2015). Time series forecasting using hybrid ARIMA and ANN models based on DWT decomposition. Procedia Computer Science , 48, 173–179. https://doi.org/10.1016/j.procs.2015.04.185
30. Kumar, M., & Thenmozhi, M. (2006). Forecasting stock indices using ARIMA–neural network hybrid models. ICFAI Journal of Applied Finance , 12(4), 55–70.
31. Lélé, S. M., & Norgaard, R. B. (2005). Practicing interdisciplinarity. BioScience , 55(11), 969–975. https://doi.org/10.1641/0006-3568 (2005)055[0969:PI]2.0.CO;2
32. McCoy, S. (1999). The practical geomancer: Discovering the earth's energy with the ancient Chinese system of Feng Shui . Destiny Books.
33. Miller, T. R., Muñoz-Erickson, T. A., & Polsky, C. (2008). Bridging the divide between social and biophysical research: A review of interdisciplinary land change studies. Human Ecology , 36(3), 429–440. https://doi.org/10.1007/s10745-008-9169-3
34. Malkiel, B. G. (2003). The efficient market hypothesis. Handbook of the Economics of Finance , 1, 1–83. https://doi.org/10.1016/S1574-0021 (02)01001-9
35. Ndlovu-Gatsheni, S. J. (2015). Epistemic freedom in Africa: Deprovincialization and decolonization. Routledge .
36. North, D. C. (1990). Institutions, institutional change and economic performance. Cambridge University Press .
37. Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock market index using fusion of machine learning techniques. Journal of Computational Science , 6, 222–230. https://doi.org/10.1016/j.jocs.2015.02.005
38. Prince, R. J. (1996). Yoruba voices: Studies in oral traditions and cultural perceptions . University of Ibadan Press.
39. Razin, A., & Collins, S. M. (1997). Real exchange rate misalignment: Definitions, measurement, and international comparisons. National Bureau of Economic Research Working Paper Series , No. 5449. https://doi.org/10.3386/w5449
40. Sadorsky, P. (2000). The effect of oil price volatility on Canadian industrial production. Energy Economics , 22(4), 413–423. https://doi.org/10.1016/S0140-9883 (99)00043-3
41. Tayefi, M., Rajaee, T., & Samadianfard, S. (2021). Hybrid machine learning models applied to monthly streamflow prediction under climate change scenarios. Water Resources Management , 35(4), 1179–1196. https://doi.org/10.1007/s11269-020-02749-y
42. Wang, J., Wang, J., Zhang, W., & Guo, H. (2018). Stock index forecasting based on a hybrid model. Omega , 40(6), 758–766. https://doi.org/10.1016/j.omega.2011.09.002
43. Yu, L., Wang, S., & Lai, K. K. (2008). Forecasting crude oil price with an EMD-based neural network ensemble learning model. Energy Economics , 30(5), 2623–2639. https://doi.org/10.1016/j.eneco.2008.05.003
44. Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing , 50, 159–175. https://doi.org/10.1016/S0925-2312 (01)00702-0
45. Zhang, Y., Zhou, W., & Wang, J. (2004). A neural network ensemble approach for financial time series forecasting. Information Sciences , 169(1–2), 39–53. https://doi.org/10.1016/j.ins.2004.02.016
46. Zondi, S. (2020). Decolonizing economics education in South Africa: A call to action. South African Journal of Higher Education , 34(4), 1–14. https://doi.org/10.20853/34-4-3747