

Machine Learning and Deep Learning Approaches for Tax and Public Revenue Forecasting in African Context: A Systematic Review

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Abstract

Forecasting tax and public revenue is a key component of fiscal planning, budget credibility and macroeconomic stability, especially in developing countries where the impact of forecast errors on public spending is particularly large. Although various machine learning (ML) and deep learning (DL) techniques have been used in the revenue forecasting problem across the globe, there is limited research that has attempted to synthesize the literature within an African context. The review is conducted in accordance with the PRISMA 2020 guideline to identify, screen and synthesize studies using some or all of at least one ML or DL model to forecast tax, customs and general government revenue in an African country. As the review was not done under paid database access, searches were made in freely accessible sources such as Google Scholar indexed publisher pages, institutional repositories, as well as IEEE Xplore. Four studies were identified from an initial pool of around 50 from nine searches and fulfilled all inclusion criteria, from Nigeria, Ghana and South Africa. It was consistently reported in included studies that ML/DL models, specifically artificial neural network (ANN) variations and hybrid models, outperformed the traditional statistical models like the ARIMA, SARIMA and Holt-Winters models. However, none of the four studies included forecasted on a daily-frequency basis, and evaluation metric choice was quite variable across different studies and no study came from the East, North or Francophone Africa region. These results suggest that there is little research on revenue forecasting using ML/DL in African context, mostly concentrated to few geographical areas and methodologically inconsistent, thus a substantive and largely unaddressed research gap.

Keywords: machine learning; deep learning; tax revenue forecasting; public revenue; Africa

Introduction

Accurate revenue forecasting is the foundation of fiscal planning, debt management and the credibility of national budgets (Leal et al., 2008). When governments systematically under- or overestimate their revenue, spending priorities are distorted, supplementary budgets become necessary and, in the long term, trust in fiscal institutions erodes; the accuracy of official revenue forecasts also varies considerably across countries depending on how forecasting is organised (Buettner & Kauder, 2010). The cost of forecasting error is greater in developing economies, where revenue bases are usually narrower and more volatile than in advanced economies. In Sub-Saharan Africa, tax revenue instability has been shown to destabilise both public investment and government consumption and to reduce the level of public investment (Ebeke & Ehrhart, 2012).

Traditional statistical methods such as the Autoregressive Integrated Moving Average (ARIMA) model and its seasonal extension, SARIMA (Box et al., 2015), have long been used to forecast revenue because of their simplicity and modest data requirements. They remain common in African revenue research; for example, ARIMA and vector autoregressive (VAR) models have recently been applied to Tanzanian tax revenue (Al-biman, 2025), and regression-based models have been used to compare quarterly and annual forecasts of Tanzanian tax revenue (Albimana & Hemed, 2022). These models are, however, largely linear and have difficulty capturing the nonlinear, volatile and structurally shifting dynamics that frequently characterise tax revenue series (Jung et al., 2018), especially where tax administration is being rapidly digitalised (Okunogbe & Santoro, 2023).

To deal with such nonlinear structure, machine learning (ML) and deep learning (DL) methods, such as random forest (Breiman, 2001), support vector regression (Drucker et al., 1997), artificial neural networks and long short-term memory (LSTM) networks (Hochreiter & Schmidhuber, 1997), have been adopted by a growing number of researchers for macroeconomic and public revenue forecasting in North America, Europe, Australia and parts of Asia (Jung et al., 2018; Wong & La, 2024; Lee et al., 2025). The evidence is not always encouraging: large comparative studies have demonstrated that ML methods cannot outperform well-specified statistical benchmarks (Makridakis et al., 2018), while empirical treasury work has revealed positive results primarily for revenue lines that are more volatile and heavily influenced by the economic environment (Wong & La, 2024).

Despite this, it is not known whether such methods of ML and DL have been widely used for forecasting tax or public revenues in Africa in general, or to what extent the applications have been methodologically consistent. Current reviews seek to answer related questions. There was no recent systematic review that combined 68 studies on the use of AI in tax compliance and evasion mitigation at a global level, nor a systematic review of machine learning applications in tax prediction generally that considered the African region as a unit of analysis. The searches performed for this review did not reveal any systematic review that specifically synthesises research on tax or public revenue forecasting using ML/DL in an African context.

This gap is important because most existing literature on ML forecasting has been developed and tested in tax environments other than those in Africa. They are characterised by large informal sectors (Medina & Schneider, 2018), comparatively recent digitisation of revenue collection systems (Okunogbe & Santoro, 2023), for instance the iTax system in Kenya, the Federal Inland Revenue Service systems in Nigeria and the Customs Division systems in Ghana, and, in many cases, limited availability of long historical data. The conclusions of ML forecasting studies undertaken in the USA, Europe or East Asia may therefore not apply directly to these conditions, and a dedicated synthesis of the African evidence is required.

This review therefore systematically identifies, appraises and synthesises empirical studies that apply ML or DL models to tax or public revenue forecasting in African countries. It maps the models that have been used, the data frequencies, sample lengths and revenue types studied (e.g., VAT, customs, corporate tax and general government revenue), the evaluation metrics applied and their consistency across studies, and the geographical distribution of the evidence across countries and sub-regions. It also draws on adjacent, non-forecasting ML applications in African tax administration to gauge the maturity of the underlying data infrastructure, and from this identifies the methodological and geographical gaps that future research should address.

Methods

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement (Page et al., 2021) for its reporting structure. The review protocol was not formally pre-registered; this is acknowledged as a limitation.

Eligibility Criteria

Studies were included if they: (1) applied at least one machine learning or deep learning model; (2) forecast the amount of tax, customs or general government revenue, rather than performing another task such as tax classification or compliance prediction; (3) used data from an African country or an African tax or customs administration; (4) were published in English as a peer-reviewed journal article, conference paper or thesis/dissertation; and (5) were available in full text through freely accessible sources or an institutional library.

Studies were excluded if they: (1) used ML/DL only to classify tax fraud, evasion or compliance without forecasting any tax or revenue quantity; (2) forecast macroeconomic aggregates (e.g., GDP, inflation or exchange rates) without a specific tax or revenue outcome variable; (3) used only traditional statistical models (ARIMA, SARIMA, VAR, BVAR, Holt-Winters or exponential smoothing) without an ML/DL comparator; (4) were not published in English; (5) could not be accessed in full text through freely available sources; or (6) were duplicate reports of the same dataset and model results.

Information Sources and Search Strategy

Because a review was not done with institutional subscriptions to databases like Scopus or Web of Science, the searches were restricted to freely available databases. These included results from Google Scholar (which can be accessed on the web), publisher platforms that allow open abstracts (such as the Applied Computational Intelligence and Soft Computing from Wiley, IEEE Xplore, Taylor & Francis and ScienceDirect repositories), institutional repositories (African University of Science and Technology repository) and ResearchGate. Google Scholar is a well-known evidence source for supplementary evidence where grey literature (theses) is involved, but should not be used as the primary source (Haddaway et al., 2015). The decision to limit sources to open sources was made on purpose and the implications of this limitation are discussed in the Limitations section.

Nine searches were made, on which were combined machine learning/deep learning terms, revenue-forecasting terms and African geographic terms. The following search strings were used: (1) "machine learning tax revenue forecasting Africa systematic review"; (2) "random forest tax revenue forecasting Nigeria"; (3) "artificial neural network government revenue forecasting Ghana Kenya"; (4) "machine learning customs revenue forecasting Uganda Tanzania Zambia"; (5) "South Africa SARS revenue forecasting machine learning XGBoost"; (6) "tax-to-GDP South Africa SARIMA artificial neural network forecasting author"; (7) "Kenya Revenue Authority machine learning revenue forecasting iTax"; (8) "hybrid machine learning model tax revenue forecasting Africa developing country"; and (9) "machine learning tax revenue forecasting Africa systematic review PRISMA novelty check". Country-specific terms (Nigeria, Ghana, Kenya, South Africa, Uganda, Tanzania and Zambia) were used throughout because initial screening showed that Africa-context studies generally name the country, rather than the continent, in their titles and abstracts.

Study Selection, Data Extraction and Synthesis

All retrieved records were screened by a single reviewer, first at title and abstract level and then at full-text level, against the eligibility criteria. Standard PRISMA practice recommends two independent reviewers, and single screening has been shown to miss more relevant studies than conventional double screening (Waffenschmidt et al., 2019); this is acknowledged as a limitation.

For each included study, the following data were extracted: country/context, revenue type, models compared, data frequency and sample period, evaluation metrics used, and the best-performing model as reported by the study's authors. Because the number of included studies was small and they varied considerably in revenue type, data frequency and evaluation metrics, a meta-analysis was not feasible, and a narrative synthesis was used instead (Popay et al., 2006).

Results and Discussion

Study Selection

In total, approximately 50 records were identified across the nine searches. Following the removal of duplicate records and of clearly non-revenue forecasting records (such as studies on the classification of tax fraud/evasion, non-African studies retrieved by the same search terms, studies on malnutrition and studies on crop-yield forecasting), 24 records were screened at the title/abstract level. Of these 11 were evaluated at full text level (10 full texts and one skimmed), and four were met at full text level and were synthesised. The process of selection of the studies was conducted following the PRISMA 2020 (Page et al., 2021) guidelines and is summarised in Table 1.

Table 1. Study Selection Process (PRISMA 2020)

Stage	Records	Notes
Identification – records found via search queries	≈ 50	Nine queries across freely accessible sources
Duplicates and clearly irrelevant records removed	26 removed	Fraud/compliance classification, unrelated ML applications, non-African studies
Screening – titles/abstracts reviewed	24	Assessed against eligibility criteria
Full-text eligibility assessment	11	Records convincingly relevant on abstract review
Excluded at full-text stage	7 excluded	No ML/DL comparator (n=4); revenue-adjacent but not forecasting (n=2); macroeconomic aggregate not revenue (n=1)
Included in synthesis	4	Nigeria (n=2), Ghana (n=1), South Africa (n=1)

Characteristics of Included Studies

The four included studies are summarised in Table 2. All four used at least one neural-network-family model (an artificial neural network, neural network autoregression, a recurrent neural network/LSTM variant or a hybrid incorporating a neural architecture) and benchmarked it against at least one classical statistical model.

Table 2. Characteristics of Included Studies

Study	Country	Revenue Type	Models Compared	Data Frequency/Period	Reported Outcome
Ajisola (2023)	Nigeria	National income tax revenue	RNN, MLP, Decision Tree vs. BATS, SARIMA, Holt-Winters, Random Walk	Monthly, multi-year	LSTM-family model reported $R^2 \approx 98.9\%$ outperforming SARIMA benchmark
Agbenyega et al. (2022)	Ghana	Customs revenue (GRA Customs Division)	NNAR(1,3), BSTS vs. ARIMA, ARIMAX	Monthly, Jan 2010-Dec 2019	NNAR(1,3) best: MSE=53.87, MAPE=0.08; ML models outperformed ARIMA/ARIMAX
Chanza et al. (2025)	South Africa	Tax-to-GDP ratio	Artificial Neural Networks vs. SARIMA	Monthly, Jan 2008 – Nov 2024	ANN achieved lower MAPE than SARIMA benchmark
Prasad et al. (2025)	Nigeria	Federal tax revenue components	MLSTM, SARIMA, MLR, hybrid MLSTM+XGBoost	Monthly, 2010-2021	Hybrid MLSTM+XGBoost best predictor, $R^2 \approx 99.7\%$

Synthesis of Findings

Models applied. All four studies included neural-network-family architectures: artificial neural networks (ANN), neural network autoregression (NNAR), LSTM models or hybrid LSTM-based models, compared with classical statistical models (ARIMA, SARIMA, Holt-Winters, Bayesian structural time series or multiple linear regression). Notably, ensemble tree-based methods appear only as a component of a hybrid model (XGBoost in Prasad et al., 2025) or as a secondary comparator (a decision tree in Ajisola, 2023), and kernel-based methods such as support vector regression do not appear at all, although both families are widely used as primary methods in the international tax and revenue-forecasting literature (Akinrinola et al., 2024; Lee et al., 2025). This indicates that African-context ML revenue-forecasting studies have so far had a narrower model focus than the international literature.

Frequency of data and type of revenue. None of the studies used daily or weekly-frequency data, and all four used monthly-frequency data. The revenues types included were national income tax (Ajisola, 2023), customs revenue (Agbenyega et al., 2022), tax-to-GDP ratio (Chanza et al., 2025) and certain elements of federal tax revenues (Prasad et al., 2025). Sample periods were roughly 9 to 17 years, and were sufficient for monthly-frequency models but not for deep learning models. This is important because evidence from Tanzania shows that the frequency of observation can impact forecasts for some of the taxes (Albimana & Hemed, 2022).

Evaluation metrics. Each one of the four studies adopted an exclusive metric to evaluate the models: MSE and MAPE were used by Agbenyega et al. (2022); MAPE was used by Chanza et al. (2025); and R^2 was stressed by Ajisola (2023) and Prasad et al. (2025). No SMAPE or WAPE were reported and no one explicitly mentioned the instability of MAPE if real revenue values are close to zero; this is a well-known issue in the general forecasting literature (Hyndman & Koehler, 2006). The lack of a unified evaluation framework is similar to the forecasting literature, where the selection

of accuracy measure can alter the ranking of competing models (Hyndman & Koehler, 2006; Makridakis et al., 2018), and it can make it hard to compare the performance of different models in different studies.

Geographic distribution. The four studies studied here are limited to West and Southern Africa countries – Nigeria (2), Ghana (1) and South Africa (1). No study that fulfilled the inclusion criteria was from East Africa or North Africa or a Francophone country in Africa, despite the fact that the majority of tax administrations and the population in Africa is in these areas.

Immediate context of literature and infrastructure. Some studies have been omitted from the core synthesis during screening because while they implement ML within tax administration in Africa, they are not used to predict the amount of revenue, but rather offer important insights on the maturity of the tax data infrastructure. Murorunkwere et al. (2023) employed ANN, logistic regression, decision tree, random forest, Gaussian naïve Bayes, and XGBoost classifiers to classify tax fraud based on the data provided by Rwanda Revenue Authority and assessed the performance of every one of them, the ANN achieved the best result. A pilot project with Zambia Revenue Authority (ZRA) has also been undertaken to employ a random forest model to guide inspection effort to high-risk consignments (Center for Effective Global Action [CEGA], n.d.). The applications demonstrate that there already is some data infrastructure and institutional capacity to support the use of ML in some African revenue authorities, but for compliance and fraud detection purposes, not for revenue forecasting purposes (Okunogbe & Santoro, 2023). This means that the lack of research on the forecasting of African ML revenue is not due to fundamental limitations on data availability, but rather due to a research and application gap.

Discussion

The aim of this review was to compile evidence regarding the application of ML/DL in forecasting tax and public revenue in African context. The overall picture is one of scarcity – some 50 records were identified but only four were included, and these four were based in three countries in West and Southern Africa. Unlike a significantly larger body of literature that applied the same techniques in North America, Europe and parts of Asia and Latin America, comparing to other architectures like random forest and support vector regression, and a variety of data frequencies and revenue types (Jung et al., 2018; Akinrinola et al., 2024; Wong & La, 2024; Lee et al., 2025).

There are three trends of studies included that are of particular interest. First, the monthly frequency of the data was the same in all four studies. The lack of high frequency (daily) data on revenues in the African literature cited here clearly provides a space for further research, so that more fine-grained administrative data can be leveraged for the analysis of revenues, as more data becomes available through, for example, the iTax in Kenya, FIRS in Nigeria and the GRA Customs Division in Ghana. These data can also reflect short-time series effects and intra-monthly volatility around the payment due date that can be hidden in the monthly data.

Second, there is not a consistent metric across the four studies, and no study utilizes any metric more robust to near zero observations of revenue, than conventional MAPE, such as SMAPE or WAPE (Hyndman & Koehler, 2006). This is an indicator of the overall lack of methodological consistency in the literature on revenue forecasting and makes it difficult to draw conclusions and compare the performance of models in the future, because models are not interchangeable and do not consistently converge in performance on the same topics.

Third, the small African-context ML revenue-forecasting related literature, so far, was found to have much narrower and distinct focus than the literature in the international context, as no study using the random forest algorithm or the support vector regression model was found, which are widely used in the literature. The lack of these models does not seem to be due to a technical or data barrier because the excluded literature on fraud detection reports that similar fraud detection models are already implemented in other similar revenue authorities in Africa, such as Rwanda and Zambia (Murorunkwere et al., 2023; CEGA, n.d.).

These outcomes provide a continent-wide perspective to a wider issue observed by literature on the use of advanced analytics in tax administration, the fact that most of the research using low frequency data and different evaluation approaches between countries (Okunogbe & Santoro, 2023; Zaim & Sahbani, 2026). These concerns are exacerbated in the African evidence summarised here by the geographic focus of available evidence.

Limitations

This review was confined to literature freely available online and subscription databases like Scopus or Web of Science were not used. A few studies that may be relevant and are behind institutional paywalls have not been picked up by the search strategy. In addition, the review protocol was not pre-registered (for example, with PROSPERO or the Open Science Framework).

Screening and eligibility assessment were performed by a single reviewer (compared with two independent reviewers as recommended by the standard PRISMA guidance, which could increase the risk of selection error (Waffenschmidt et al., 2019)).

The literature search has been restricted to English language literature and so there may be Francophone or Lusophone African literature that is relevant but not found. This is a constraint, especially if considering that none of the studies included represents a Francophone African country.

The search was carried out on a single occasion. The field is rapidly changing and the search should be updated on a regular basis as tax administration in Africa continues to be digitised.

The review is exploratory and maps a sparse literature, and does not aim at providing a quantitative synthesis (meta-analysis) of the literature, since only four studies have been included.

Conclusion and Recommendations

The findings from this systematic review indicated that there is little research work in the field of machine learning and deep learning applied to tax forecasting and public revenue forecasting in Africa. Most of the studies are geographically limited to West and Southern Africa, using only monthly data, and focus on neural-network-family models with variable evaluation practices. At the same time, tax fraud detection and customs risk-scoring systems in Rwanda and Zambia show that the infrastructure for data analysis already exists in several African revenue authorities, where it was developed for fraud detection and customs risk management. The scarcity of ML revenue-forecasting research identified in this review therefore does not appear to stem from a fundamental lack of infrastructure.

Future primary research could be strengthened by: (1) using daily or weekly data instead of monthly data where digitalised systems allow; (2) considering a wider range of models beyond neural architectures, such as the ensemble and kernel-based models used in the global literature but not identified in this review; (3) evaluating results consistently within a framework robust to near-zero values, including RMSE, MAE, SMAPE or WAPE, and R^2 , with a justification for the choice of metrics; and (4) expanding empirical coverage to East Africa, North Africa and Francophone Africa, where no ML/DL revenue-forecasting study meeting the inclusion criteria of this review was found. Future systematic reviews on this topic would benefit from access to subscription databases and from two independent reviewers, who could validate and extend the exploratory results presented here.

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