Preprints.org

Review

Not peer-reviewed version

# From ARIMA to Chaos-Enhanced LSTM: Methodological Progression of Philippine Forecasting Models Across Energy, Agriculture, Finance, and Health

Adrian M. Velasco *

Posted Date: 18 March 2026

doi: 10.20944/preprints202603.1342.v1

Keywords: time series forecasting; ARIMA; machine learning; LSTM; Philippines

Preprints.org is a free multidisciplinary platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC.

Copyright: This open access article is published under a Creative Commons CC BY 4.0 license, which permit the free download, distribution, and reuse, provided that the author and preprint are cited in any reuse.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 18 March 2026 doi:10.20944/preprints202603.1342.v1

Disclaimer/Publisher's Note: The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.

*Review*

# From ARIMA to Chaos-Enhanced LSTM: Methodological Progression of Philippine Forecasting Models Across Energy, Agriculture, Finance, and Health

**Adrian M. Velasco**

Department of Mathematics and Statistics, Central Luzon State University, Science City of Muñoz, Nueva Ecija, Philippines; adrian.velasco@clsu.edu.ph

**Abstract**

Forecasting research in the Philippines has evolved from classical time-series analysis toward comparative machine learning and selected hybrid nonlinear models. Across energy, agriculture, health, and finance, this progression reflects changing data complexity, forecasting goals, and temporal behavior rather than simple replacement of older methods. Early studies on electricity consumption, provincial demand, and coal production relied on ARIMA-type models because the series were aggregate, limited, and well suited to interpretable linear frameworks. Later work on crop production, monthly peak demand, and disease incidence adopted comparative designs that evaluated seasonal statistical models alongside neural and machine-learning approaches, showing added value when seasonality was less stable and nonlinear dependence was more evident. The progression culminated in chaos-enhanced LSTM modeling for the Philippine stock exchange index, where nonlinear state reconstruction became methodologically defensible. Overall, ARIMA remains sufficient for largely linear seasonal signals, whereas machine learning and hybrid methods are justified for more complex dynamics.

**Keywords:** time series forecasting; ARIMA; machine learning; LSTM; Philippines

## Introduction

Forecasting practice in Philippine applied research has followed a clear methodological progression rather than a sudden shift from one paradigm to another. Early work was dominated by classical univariate time-series methods because many local datasets were official, aggregate, regularly spaced, and not especially large. Under those conditions, ARIMA-type models, seasonal ARIMA, and exponential smoothing were natural starting points because they offered parsimonious structure, diagnostic transparency, and defensible extrapolation. In the broader forecasting literature, these properties remain central reasons why classical methods continue to serve as strong baselines, particularly when the series is short to moderate in length and the dominant structure is trend, seasonality, or lag dependence rather than complex nonlinear behavior (Box et al., 2015; de Gooijer & Hyndman, 2006; Hyndman & Athanasopoulos, 2021).

The Philippine studies under review show that forecasting practice did not evolve by discarding classical models, but by widening the model space as forecasting problems became more demanding. In energy, early studies relied on ARIMA for national electricity consumption, provincial electricity demand, and coal production and consumption, while later work on monthly system peak demand explicitly compared seasonal ARIMA with neural-network approaches. In agriculture, seasonal statistical models were first compared against one another before machine-learning models were introduced in later work. In health, comparative forecasting became a tool not only for prediction but also for surveillance inference, especially in pandemic-period underreporting analysis. In finance, the

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 18 March 2026 doi:10.20944/preprints202603.1342.v1



move toward chaos-enhanced LSTM signaled a further step in which the generating process itself was treated as nonlinear and state-dependent rather than adequately summarized by raw linear lags alone (Parreño, 2022a, 2022b, 2022c, 2023a, 2023b, 2024a, 2024b, 2024c, 2025; Parreño & Anter, 2024).

What emerges from this progression is a methodological story about matching model complexity to data complexity. When the signal is largely linear and seasonal, classical methods remain appropriate and often sufficient. When the temporal process becomes more nonlinear, irregular, or structurally unstable, comparative machine learning becomes more useful. When there is reason to believe that the observed series is a scalar trace of a higher-dimensional nonlinear system, hybrid and chaos-informed approaches become methodologically defensible. The central issue, therefore, is not whether one class of model is universally superior, but when the data justify moving from a simpler to a more complex framework (Zhang, 2003; Khashei & Bijari, 2011; Kontopoulou et al., 2023; Sezer et al., 2020).

## Theoretical Background

Classical time-series forecasting rests on the premise that temporal dependence can be represented through relatively compact stochastic structures. ARIMA and SARIMA models express the series through autoregressive memory, moving-average shock propagation, differencing, and where needed, seasonal operators. Their enduring value lies not only in forecast generation but in the interpretability of the modeling process itself: one can inspect stationarity, test residual autocorrelation, evaluate forecast errors, and justify the chosen structure in terms that are intelligible to both statisticians and applied decision-makers. Exponential smoothing and Holt-Winters methods address a related problem from a state-updating perspective and are particularly effective when the series is dominated by evolving level, trend, and seasonality rather than by complex nonlinear interactions (Box et al., 2015; Hyndman & Athanasopoulos, 2021).

Machine learning enters forecasting when temporal structure is difficult to capture with linear lag operators alone. Neural network autoregression, feed-forward neural networks, random forests, echo state networks, and related learners are useful when interactions among lags are nonlinear, when seasonal patterns vary in amplitude, or when threshold-like and asymmetric behavior matters. Even so, the forecasting literature consistently shows that flexibility alone does not guarantee superiority. The M4 and M5 competition findings reinforced the importance of benchmarking advanced models against strong statistical baselines rather than assuming that more complex architectures automatically yield better generalization (Makridakis et al., 2020, 2022). A modern review of ARIMA versus machine-learning approaches likewise emphasizes that performance depends on the data regime, with machine learning tending to add value when the process is more nonlinear, higher-dimensional, or more structurally heterogeneous (Kontopoulou et al., 2023).

Hybrid and nonlinear approaches rest on a stronger theoretical claim. Hybrid ARIMA-neural frameworks assume that the observable sequence may contain both linear and nonlinear components, so that a statistical model can capture structured autocorrelation while a neural learner models the residual nonlinear signal (Zhang, 2003; Khashei & Bijari, 2011). A still more ambitious position comes from nonlinear dynamics, where Takens' theorem provides the basis for reconstructing phase space from a univariate time series, and LSTM offers a recurrent architecture suited to long-range temporal dependencies (Takens, 1981; Hochreiter & Schmidhuber, 1997). This combination is most compelling when the observed series is believed to be generated by a nonlinear dynamic system rather than by a predominantly linear stochastic process.

## Comparative Methodological Review

*Energy*

The earliest stage of the progression is especially visible in energy forecasting. National electricity consumption was modeled with ARIMA using official Philippine data, and the published article shows a straightforward Box-Jenkins workflow centered on identification, estimation,

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 18 March 2026 doi:10.20944/preprints202603.1342.v1



diagnostic checking, and out-of-sample evaluation (Parreño, 2022a). Provincial electricity demand in Davao del Sur was handled in much the same way, with the study selecting an ARIMA model with drift for forecasting after standard residual checks and model comparison (Parreño, 2022b). A similar methodological template also appeared in the coal production and coal consumption study, where separate ARIMA models were selected for the two series and evaluated through residual analysis and forecast performance measures (Parreño, 2022c). These studies illustrate a period in which Philippine forecasting practice was appropriately anchored in classical univariate modeling because the underlying datasets were aggregate, policy-relevant, and limited enough that interpretability and statistical diagnostics were stronger priorities than algorithmic flexibility.

The stationarity study on per-capita electricity consumption in ASEAN countries refined this classical phase by showing that the adequacy of ARIMA-type modeling depends heavily on diagnostic assumptions rather than on routine model fitting alone. That work focused on structural breaks and unit-root behavior across country-level electricity series and reinforced the point that differencing, stationarity assessment, and break-aware diagnostics are not technical preliminaries to be rushed through, but core methodological choices that shape the legitimacy of downstream forecasting or inference (Parreño, 2024a). In a broader methodological sense, this study sharpened the conditions under which classical time-series analysis remains appropriate in energy research: not merely when data are available, but when their persistence structure can be modeled meaningfully after accounting for nonstationarity and breaks.

A more advanced stage appeared in the study of total non-coincidental monthly system peak demand. There, seasonal ARIMA was no longer treated as the sole natural framework. Instead, it was compared directly with a feed-forward neural network expressed through NNAR notation. The article reports that the neural model achieved lower RMSE, MAE, and MAPE than the SARIMA benchmark and better captured the positive trend in the series, leading the author to conclude that the neural specification outperformed the seasonal statistical model for this monthly demand application (Parreño, 2023a). Methodologically, this was an important transition: the problem had shifted from fitting a single interpretable model to testing whether nonlinear forecasting could add value in a higher-frequency demand environment. That transition is consistent with broader reviews showing that machine-learning methods become increasingly relevant in electricity and load forecasting when demand patterns are more complex, operationally dynamic, and difficult to summarize through fixed seasonal linear structures (Román-Portabales et al., 2021).

*Agriculture*

Agricultural forecasting in the Philippine setting shows that methodological progression is not a simple one-way climb from old to new. In the quarterly rice and corn study, the comparison was still entirely within the classical family, but it was already comparative in spirit. The article summary reports that Holt-Winters with additive seasonality outperformed SARIMA for both rice and corn, achieving lower RMSE and MAPE. This is methodologically important because it demonstrates that when the signal is strongly seasonal and relatively smooth at the quarterly scale, exponential smoothing can be more effective than a more formally parameterized stochastic model (Parreño, 2023b). The lesson is that progression in forecasting methodology should not be mistaken for a hierarchy in which more elaborate models are always better. Sometimes the most appropriate advance is not greater complexity but more careful alignment between model structure and seasonal behavior.

The next step in agriculture came when the model space expanded beyond classical seasonal methods. In the later crop study, four machine-learning models were compared for forecasting Philippine rice and corn production, namely random forest, echo state network, neural network autoregression, and autoregressive support vector machine. The published abstract and article summary report that random forest delivered the lowest MAE, RMSE, and MAPE for both crops, outperforming the other machine-learning candidates and indicating that flexible nonlinear mapping added useful predictive value in this setting (Parreño & Anter, 2024). This development reflects a

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 18 March 2026 doi:10.20944/preprints202603.1342.v1



meaningful methodological broadening: the target series were no longer treated as processes to be described only through trend and seasonality, but as patterns potentially shaped by nonlinear relationships better captured by algorithmic learners. That trajectory aligns with agricultural forecasting reviews showing that machine learning is particularly useful when crop behavior reflects nonlinear responses, heterogeneous influences, and more complex data-generating relationships than classical seasonal models can easily encode (van Klompenburg et al., 2020; Jabed et al., 2024).

*Health*

The health studies reveal a further methodological shift because forecasting was used not only for projection but also for surveillance interpretation. In the measles study, SARIMA, Holt-Winters, echo state networks, and NNAR were compared on weekly Philippine incidence data. The article text reports that NNAR yielded the lowest prediction errors across RMSE, MAPE, and MAE and was judged the most effective model among the four alternatives (Parreño, 2025). This result is methodologically plausible. Weekly infectious-disease data often contain seasonal recurrence, abrupt changes in magnitude, and nonlinear epidemiological dynamics, so a flexible nonlinear autoregressive structure can outperform models that assume more stable linear seasonal behavior. The broader epidemiological forecasting literature likewise shows that no single model class dominates across all disease settings, but neural and related methods can be especially useful when incidence patterns are irregular or shaped by multiple interacting influences (Datilo et al., 2019; Xian et al., 2023). (ResearchGate)

The pandemic underreporting study moved forecasting into an even more conceptually ambitious role. Rather than treating the forecast as the end product, the study used comparative forecasting to estimate expected disease incidence under normal reporting conditions and then contrasted those forecasts with pandemic-period observations to detect likely surveillance disruption. The paper reports that, across many diseases, NNAR frequently emerged as the best-performing model and that the evidence pointed to significant underreporting during the COVID-19 period (Parreño, 2024c). Methodologically, this matters because it shows that forecasting can function as a comparative baseline for epidemiological system diagnosis, not merely as a forward-looking prediction device. In other words, once forecasting is embedded in a surveillance framework, model selection must be judged not only by predictive accuracy but also by the credibility of the counterfactual benchmark it produces.

*Finance*

The financial application marks the strongest break from the earlier univariate classical paradigm. In the stock-index study, the modeling strategy explicitly combined chaos theory and LSTM, using Takens' embedding theorem to reconstruct the phase space of the Philippine Stock Exchange Index before applying sequence learning. The Springer abstract states that this approach was adopted because traditional linear models were viewed as limited for capturing the intricate nonlinear behavior of the series, and that the resulting Takens–LSTM framework was able to follow the overall market trend with high fidelity despite deviations in volatile periods (Parreño, 2024b). This is not merely a more complex forecasting model. It represents a different understanding of what the data are: not just a lagged scalar sequence, but an observable generated by an underlying nonlinear dynamic system.

This direction is consistent with broader financial forecasting literature, where deep learning and nonlinear models are most persuasive when the target series is volatile, nonstationary, and likely governed by complex temporal dependencies. Review work in finance shows that LSTM and related deep architectures have become prominent precisely because they can exploit nonlinear and long-range temporal structure that is difficult to capture with simple linear models (Sezer et al., 2020). At the same time, the methodological burden is much higher: nonlinear reconstruction, embedding choices, training design, and evaluation must all be justified carefully. The lesson from the Philippine financial study is therefore not that chaos-enhanced LSTM should replace ARIMA everywhere, but

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 18 March 2026 doi:10.20944/preprints202603.1342.v1



that such a model becomes reasonable when the domain itself provides a substantive argument for nonlinear state dependence.

*Cross-Domain Lessons*

Several lessons cut across domains. First, ARIMA-type models are sufficient when the series is relatively short, the dominant dependence is linear, seasonality is stable, and the forecasting objective values interpretability, diagnostic clarity, and transparency for policy communication. This describes much of the early Philippine energy work and part of the crop-forecasting literature. Under those conditions, classical methods are not weak approximations waiting to be replaced; they are proportionate models aligned with the structure of the data and the institutional context of use (Box et al., 2015; Hyndman & Athanasopoulos, 2021; Parreño, 2022a, 2022b, 2022c, 2023b).

Second, machine learning adds value when the forecasting environment becomes more nonlinear, higher-frequency, or structurally heterogeneous. That pattern appears in monthly peak demand, agricultural production under broader comparative modeling, weekly measles incidence, and pandemic-period disease comparison. In these contexts, machine learning was not adopted simply because it was modern, but because the forecasting problem began to exceed what static linear trend-seasonal formulations could comfortably represent. This is broadly consistent with comparative reviews in energy, agriculture, and generic forecasting, all of which emphasize that flexible models become more attractive as signal complexity rises, but only when they are evaluated against credible statistical baselines (Kontopoulou et al., 2023; Román-Portabales et al., 2021; van Klompenburg et al., 2020; Jabed et al., 2024).

Third, hybrid and nonlinear approaches become justifiable only when the extra complexity is earned by the data and the domain. The key justifications include persistent nonlinear residual structure after fitting classical models, repeated superiority of nonlinear learners in rolling or holdout evaluation, theoretical reasons to believe that the observed series reflects hidden state dynamics, or a domain such as finance where volatility and nonlinear dependence are substantive rather than incidental. Hybrid ARIMA-neural models and chaos-informed LSTM frameworks are most persuasive under those stronger conditions, not as general-purpose replacements for well-performing classical models (Zhang, 2003; Khashei & Bijari, 2011; Takens, 1981; Sezer et al., 2020).

## Recommended Model Selection Framework

A practical model-selection framework for Philippine forecasting should begin with diagnosis rather than algorithm choice. The first step is to inspect frequency, sample size, seasonal patterning, breaks, missingness, and stationarity. If the series is short, low-dimensional, and dominated by regular trend-seasonal behavior, the analyst should start with classical baselines such as seasonal naïve, Holt-Winters, ETS, ARIMA, or SARIMA. This is not merely tradition; it is good methodological discipline because strong baselines establish whether the data actually require greater complexity (Box et al., 2015; Hyndman & Athanasopoulos, 2021).

The second step is comparative escalation. If classical models leave patterned residuals, fail to capture seasonal amplitude changes, or underperform in time-ordered validation, then machine-learning approaches become appropriate candidates. In such cases, NNAR, feed-forward neural networks, random forests, echo state networks, or support vector variants can be tested, with performance assessed through holdout or rolling-origin validation rather than in-sample fit. This is the stage exemplified by the Philippine peak-demand, crop, and measles studies, where gains from flexible learning were tied to concrete forecasting improvements rather than theoretical enthusiasm alone (Parreño, 2023a, 2024b, 2025; Parreño & Anter, 2024).

The third step is structural justification. Hybrid and nonlinear dynamical methods should be reserved for the most demanding cases, especially when the domain itself suggests that the observed series is produced by a nonlinear system with latent state dynamics. In those cases, delay embedding, phase-space reconstruction, or hybrid residual modeling can be methodologically warranted. However, their use should be supported by clear evidence of forecast gain, not by novelty alone. The

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 18 March 2026 doi:10.20944/preprints202603.1342.v1



Philippine stock-index study provides an example of such justification because the methodology explicitly linked nonlinear reconstruction to a financial series whose behavior is difficult to treat as merely linear and seasonal (Parreño, 2024b; Deyle & Sugihara, 2011; Sezer et al., 2020).

A final principle concerns deployment. The best forecasting model is not always the one with the lowest error in a single experiment, but the one whose performance is stable, explainable enough for its purpose, and feasible for the institution that will maintain it. In public-sector, educational, and health settings, a slightly less accurate but more transparent model may still be preferable if it can be updated regularly, audited, and communicated to decision-makers. Forecasting methodology, therefore, should be selected not only on statistical grounds but also on operational suitability. That is the broader lesson that emerges from the Philippine progression from classical forecasting to comparative machine learning and then to hybrid nonlinear modeling.

## Conclusions

The evolution of Philippine forecasting models across energy, agriculture, health, and finance shows a movement from parsimonious linear time-series analysis toward increasingly comparative and nonlinear frameworks. Classical ARIMA-type models anchored the early phase because they were well matched to official aggregate datasets and to institutional demands for interpretability. Comparative machine-learning models emerged when forecasting problems became more nonlinear, more frequent, or more operationally sensitive. Hybrid and chaos-enhanced methods appeared only at the point where the data and domain jointly supported a stronger claim about hidden nonlinear structure. Seen in this way, forecasting practice did not simply become more advanced over time; it became more selective about when additional complexity is warranted.

The central methodological lesson is that model choice should be driven by evidence about the structure of the series, not by allegiance to a particular modeling tradition. ARIMA remains sufficient when the process is largely linear and seasonal. Machine learning adds value when nonlinear dependence and richer temporal patterning matter. Hybrid and nonlinear dynamical methods become justifiable when simpler models repeatedly fail and when there is substantive reason to believe that the observed data reflect a more complex underlying system. This staged perspective offers a coherent framework for future Philippine forecasting work and helps explain why the transition from ARIMA to chaos-enhanced LSTM was not abrupt, but the logical outcome of increasingly complex forecasting questions.

## References

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: Forecasting and control* (5th ed.). Wiley.

Datilo, P. M., Ismail, Z., & Dare, J. (2019). A review of epidemic forecasting using artificial neural networks. *International Journal of Epidemiologic Research, 6*(3), 132–143. https://doi.org/10.15171/ijer.2019.24

de Gooijer, J. G., & Hyndman, R. J. (2006). 25 years of time series forecasting. *International Journal of Forecasting, 22*(3), 443–473. https://doi.org/10.1016/j.ijforecast.2006.01.001

Deyle, E. R., & Sugihara, G. (2011). Generalized theorems for nonlinear state space reconstruction. *PLoS ONE, 6*(3), e18295. https://doi.org/10.1371/journal.pone.0018295

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780.

Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and practice* (3rd ed.). OTexts.

Jabed, M. A., Murad, M. A. A., Hossain, M. E., Akter, S., Moon, N. N., Miah, M. A. M., & Shatabda, S. (2024). Crop yield prediction in agriculture: A comprehensive review of machine learning and deep learning approaches, with insights for future research and sustainability. *Heliyon, 10*(24), e40836. https://doi.org/10.1016/j.heliyon.2024.e40836

Khashei, M., & Bijari, M. (2011). A novel hybridization of artificial neural networks and ARIMA models for time series forecasting. *Applied Soft Computing, 11*(2), 2664–2675. https://doi.org/10.1016/j.asoc.2010.10.015

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 18 March 2026 doi:10.20944/preprints202603.1342.v1



Kontopoulou, V. I., Panagopoulos, A. D., Kakkos, I., & Matsopoulos, G. K. (2023). A review of ARIMA vs. machine learning approaches for time series forecasting in data driven networks. *Future Internet, 15*(8), 255. https://doi.org/10.3390/fi15080255

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2020). The M4 competition: 100,000 time series and 61 forecasting methods. *International Journal of Forecasting, 36*(1), 54–74. https://doi.org/10.1016/j.ijforecast.2019.04.014

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2022). M5 accuracy competition: Results, findings, and conclusions. *International Journal of Forecasting, 38*(4), 1346–1364. https://doi.org/10.1016/j.ijforecast.2021.11.013

Parreño, S. J. E. (2022a). Forecasting electricity consumption in the Philippines using ARIMA models. *International Journal of Machine Learning and Computing, 12*(6), 279–285. https://doi.org/10.18178/ijmlc.2022.12.6.1112

Parreño, S. J. E. (2022b). Analysis and forecasting of electricity demand in Davao del Sur, Philippines. *International Journal on Soft Computing, Artificial Intelligence and Applications, 11*(1/2), 25–33. https://doi.org/10.5121/ijscai.2021.11202

Parreño, S. J. E. (2022c). Application of time series analysis in forecasting coal production and consumption in the Philippines. *ICTACT Journal on Soft Computing, 13*(1), 2798–2804. https://doi.org/10.21917/ijsc.2022.0398

Parreño, S. J. (2023a). Forecasting the total non-coincidental monthly system peak demand in the Philippines: A comparison of seasonal autoregressive integrated moving average models and artificial neural networks. *International Journal of Energy Economics and Policy, 13*(5), 544–552.

Parreño, S. J. E. (2023b). Forecasting quarterly rice and corn production in the Philippines: A comparative study of seasonal ARIMA and Holt-Winters models. *ICTACT Journal on Soft Computing, 14*(2), 3224–3231. https://doi.org/10.21917/ijsc.2023.0452

Parreño, S. J. E. (2024a). Assessing the stationarity of per capita electricity consumption: Time series analysis in ASEAN countries. *International Journal of Energy Economics and Policy, 14*(2), 46–52. https://doi.org/10.32479/ijeep.15357

Parreño, S. J. (2024b). Chaos theory enhanced LSTM model of the Philippine stock exchange index. *SN Computer Science, 5*, 779. https://doi.org/10.1007/s42979-024-03160-1

Parreño, S. J. (2024c). Evaluating the underreporting of diseases in the Philippines during the COVID-19 pandemic through comparative forecast analysis. *Research Square*. https://doi.org/10.21203/rs.3.rs-3837011/v1

Parreño, S. J. E., & Anter, M. C. J. (2024). New approach for forecasting rice and corn production in the Philippines through machine learning models. *Multidisciplinary Science Journal, 6*(9), e2024168. https://doi.org/10.31893/multiscience.2024168

Parreño, S. J. E. (2025). Forecasting measles incidence in the Philippines: A comparative analysis of SARIMA, Holt-Winters, ESN, and NNAR models. *Multidisciplinary Science Journal, 7*(7), 2025356. https://doi.org/10.31893/multiscience.2025356

Román-Portabales, A., López-Nores, M., & Pazos-Arias, J. J. (2021). Systematic review of electricity demand forecast using ANN-based machine learning algorithms. *Sensors, 21*(13), 4544. https://doi.org/10.3390/s21134544

Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. *Applied Soft Computing, 90*, 106181. https://doi.org/10.1016/j.asoc.2020.106181

Takens, F. (1981). Detecting strange attractors in turbulence. In D. Rand & L.-S. Young (Eds.), *Dynamical systems and turbulence, Warwick 1980* (Lecture Notes in Mathematics, Vol. 898, pp. 366–381). Springer. https://doi.org/10.1007/BFb0091924

van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. *Computers and Electronics in Agriculture, 177*, 105709. https://doi.org/10.1016/j.compag.2020.105709

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 18 March 2026 doi:10.20944/preprints202603.1342.v1



Xian, X., Wang, L., Wu, X., Tang, X., Zhai, X., Yu, R., Qu, L., & Ye, M. (2023). Comparison of SARIMA model, Holt-Winters model and ETS model in predicting the incidence of foodborne disease. *BMC Infectious Diseases, 23*, 803. https://doi.org/10.1186/s12879-023-08799-4

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

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.