Zero-shot forecasting of epidemics

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Abstract

Accurate epidemic forecasting is critical for mitigating the global burden of infectious diseases, enabling timely interventions and optimal resource allocation. While conventional forecasting approaches can effectively model the temporal trajectory of epidemic dynamics, they rely on task-specific learning from historical observations, which are often scarce and limited. Recently, pre-trained Large Language Models (LLMs) have emerged as powerful foundation tools for zero-shot time series forecasting across diverse domains, eliminating the need for retraining on task-specific data. In this study, we conduct a comprehensive evaluation of LLM-based foundation models to capture the complex dynamics of epidemic incidences across multiple temporal horizons. Our analysis not only benchmarks these models against statistical and deep learning frameworks, but also identifies which architectural designs of LLM models are suitable for epidemic forecasting. The empirical results conducted on eleven epidemic datasets spanning three diseases from distinct geographical locations highlight that TimeGPT and TiRex models exhibit superior generalization capabilities. These findings underscore the potential of zero-shot LLM-based epidemic forecasting to support effective decision-making.

1 Introduction

Epidemic forecasting plays a vital role in providing situational awareness and guiding policy makers during public health crises [20]. Accurate short-term predictions of disease outcomes are particularly critical, as they enable effective allocation of resources and the design of timely intervention strategies, thereby mitigating risks and reducing the overall disease burden [22]. Epidemic forecasting models are broadly divided into mechanistic (e.g., SIR-type) and statistical approaches (including machine learning models), with the former suited for long-term scenario analysis and the latter for short-term trend adaptation [16]. Traditionally, epidemic forecasting tasks have been approached using statistical methods like Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing (ETS), and Theta, which offer interpretability but often struggle with non-linear patterns and long-range dependencies [2]. In recent years, deep learning models, particularly Long Short-Term Memory (LSTM) networks, Neural Hierarchical Interpolation for Time Series (N-HiTS), and Transformer-based architectures, have demonstrated improved performance by capturing complex temporal structures and nonstationarities in data [13]. However, machine learning models require task-specific training, such as using historical disease incidence data from Hong Kong to forecast its future disease dynamics. In contrast, generative pre-trained models utilize probabilistic methods and large-scale datasets to serve as foundation models, capable of handling diverse tasks without requiring retraining

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NeurIPS 2025 Workshop on Recent Advances in Time Series Foundation Models (BERT^{2}S).

[24]. This shift has spurred efforts to develop general-purpose pre-trained models for zero-shot time-series forecasting in various applied domains [15].

Amid this evolving landscape, Large Language Models (LLMs), originally designed for natural language processing tasks, have emerged as promising tools for a broader range of sequence modeling applications [15]. These models, trained on vast corpora of sequential data, possess strong representational capacity and an inherent ability to model long-range dependencies. Recent advancements have shown that LLMs can be repurposed for time series forecasting of chaotic systems [24], treating time series as sequences of tokens. This perspective opens the door to zero-shot forecasting, where pre-trained models are used directly for prediction without requiring additional fine-tuning on the target dataset. Such models have seen some initial success in forecasting real-world time series, including pandemic time series [10, 8]. However, their effectiveness on epidemiological forecasting of other infectious diseases such as dengue, malaria, and influenza, particularly across short- and long-term horizons, remains largely unexplored.

Motivated by the above, this study conducts a comprehensive evaluation of pre-trained LLM-based models in the context of (infectious) epidemic time series forecasting. By examining the performance of LLMs in a zero-shot setting, our main contributions are as follows:

1. We present a large-scale evaluation of pre-trained LLM-based foundation models for various epidemic time series forecasting, benchmarking them against statistical and deep learning baselines.
2. We design an evaluation framework that reflects real-world forecasting demands by partitioning the task into short-, medium-, and long-horizon forecasts, and implementing a rolling-window strategy to ensure temporal robustness and fair comparisons.
3. We investigate the zero-shot forecasting ability of pre-trained LLMs, addressing whether they can be effectively adapted without task-specific training, how they compare with established approaches across horizons, and which architectural designs are best suited for epidemic forecasting.

Our findings highlight both the strengths and limitations of LLM-based approaches, revealing their capacity to generalize and capture long-term temporal dependencies, while providing practical guidance for integrating them into epidemic forecasting pipelines.

2 Material and Methods

This section provides a brief overview of the real-world epidemic datasets used in our analysis, along with a description of the baseline models and LLM-based forecasting approaches evaluated in this study.

2.1 Epidemic Datasets

We analyze eleven real-world epidemic datasets collected from publicly available sources [16]. These datasets capture the number of reported infections for a diverse range of diseases, including dengue, malaria, and influenza, across different geographical locations. Each dataset varies in both historical length and temporal granularity. Specifically, nine datasets provide weekly counts of infected individuals for a given disease, whereas the remaining two contain aggregated monthly case counts. For example, the dengue dataset from Hong Kong represents the total number of infections reported in every month across the country, while the Ahmedabad dengue dataset records weekly incidence rates per 10^4 population. To characterize the structural properties of these epidemic time series, we examine several statistical features, including stationarity, long-term dependency (LTD), linearity, and seasonality. Stationarity is assessed using the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, while long-range dependence is quantified via the Hurst exponent. Linearity is examined using Teraesvirta's neural network test, and recurring seasonal patterns are detected using the combined Ollech and Webel seasonality test. The results of these statistical tests, summarized in Table 1, reveal that most epidemic time series are non-stationary, exhibit non-linear dynamics, with significant long-term dependencies, and contain seasonal fluctuations of varying frequencies. This comprehensive understanding forms the foundation for selecting and evaluating appropriate forecasting models in the subsequent sections.

Table 1: Epidemic data characteristics. The green circles represent the presence of the feature, while the red ones represent its absence.

Disease	Location	Granularity	Time span	Observ-ations	Statistical properties			
					Stationary	LTD	Linear	Seasonal
Dengue	Venezuela	1 week	2002-2014	660	🔴	🟢	🟢	🟢
	Singapore	1 week	2000-2015	838	🔴	🟢	🟢	🔴
	Ahmedabad	1 week	2005-2012	424	🔴	🟢	🔴	🔴
	Bangkok	1 month	2003-2017	180	🔴	🟢	🔴	🟢
	Colombia	1 week	2005-2016	626	🔴	🟢	🔴	🟢
	Hong Kong	1 month	2002-2017	192	🔴	🟢	🟢	🟢
Influenza	Australia	1 week	1947-2015	974	🔴	🟢	🔴	🟢
	Mexico	1 week	2000 - 2015	830	🔴	🟢	🔴	🔴
	Japan	1 week	1998 - 2015	964	🟢	🟢	🔴	🟢
Malaria	Colombia	1 week	2005 - 2016	626	🔴	🟢	🟢	🟢
	Venezuela	1 week	2002 - 2014	669	🔴	🟢	🔴	🟢

2.2 Foundation Models for Forecasting

In this study, we choose Chronos, TimeGPT, Lag-Llama, and TiRex frameworks to represent the class of pre-trained foundation models owing to their state-of-the-art performance in diverse time series forecasting tasks [24, 15].

Chronos is a pre-trained model that leverages text-to-text T5 Transformers, augmented with a scaling and quantization layer to convert time-dependent continuous-valued observations into a discrete set of tokens [1]. This LLM-based framework is trained on a diverse set of real-world and synthetic time series datasets. We evaluate four variants of the Chronos architecture, categorized based on the T5 model size as Chronos-Tiny (8M), Chronos-Mini (20M), Chronos-Small (46M), and Chronos-Base (200M).

TimeGPT is a Transformer-based foundation model designed specifically for time series forecasting [9]. The framework utilizes a self-attention mechanism to capture temporal patterns in historical observations. It incorporates local positional encoding, processes inputs through a multi-layer encoder-decoder with residual connections and normalization, and maps the output to the desired forecast window via a linear layer.

Lag-Llama is a decoder-only Transformer architecture that employs lag-based features as inputs [19]. The model processes these input tokens through masked Transformer decoder layers enhanced with RMSNorm and Rotary Positional Encoding (RoPE), effectively capturing temporal dependencies in sequential data.

TiRex is a decoder-only time series model built on an xLSTM architecture [3]. This framework tokenizes the input sequence via scaling and patching operations, which are processed with stacked xLSTM blocks to generate accurate forecasts for the time series.

2.3 Baseline Forecasting Models

To comprehensively evaluate the epidemic forecasting capabilities of pre-trained foundation models, we benchmark their performance against a suite of classical statistical approaches and advanced deep learning frameworks. Among the statistical baselines, we include the Naive or persistence model [17], the linear ARIMA model [4], and the ETS method [12]. The machine learning baselines comprise ensemble models, such as extreme gradient boosting (XGBoost) [7], light gradient-boosting machine (LightGBM) [14], and categorical boosting (CatBoost) [18], along with decomposition-based linear models such as DLinear [23]. For deep learning architectures, we consider LSTM networks [11], N-HiTS [5], attention-based Transformer models [21], and multilayer perceptron-based frameworks such as TSMixer [6].

3 Experimental Setup and Results

In our analysis, we evaluate the forecasting capabilities of the foundation models and baseline architectures by adopting a rolling window approach across three distinct temporal horizons. For the long-term forecasting task, we partition the epidemic dataset into 75% training, 15% validation, and 10% testing observations, allowing the models to focus on capturing long-range trends and seasonal

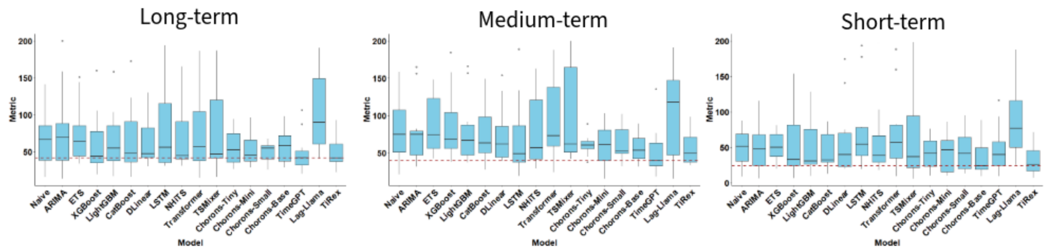

Figure 1: Boxplots comparing the long-term (left panel), medium-term (middle panel), and short-term (right panel) forecasting performance of foundation models and baseline architectures in terms of SMAPE metric. In the plot, the dashed brown line corresponds to the lowest median value among all the models.

patterns. The medium-term forecasting task employs a temporal split of 80% training, 15% validation, and 5% testing, where the objective is to predict semi-long-term trends in the epidemic data. For the short-term horizon, we utilize 90% observations for training, 8% observations for validation, and 2% observations for testing and assess the performance of the models in predicting the short-term fluctuations in epidemic incidence cases. This multi-horizon evaluation provides a comprehensive assessment of model robustness and adaptability across varying forecast durations. Furthermore, we employ four key performance metrics, namely symmetric Mean Absolute Percentage Error (sMAPE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Scaled Error (MASE), to evaluate the point forecasting performance of the models. The mathematical formulation of these metrics is discussed in Appendix A.1. By definition, the minimum value of these performance measures suggests the 'best' model.

Our empirical results present a comprehensive evaluation of baseline and foundation models, with a particular focus on identifying which foundation models are best suited for epidemic forecasting. The SMAPE metric values, as summarized in Fig. 1, demonstrate that pre-trained foundation models consistently achieve superior performance over statistical and deep learning architectures across all temporal horizons. Among the LLM-based frameworks, TimeGPT and TiRex achieve the lowest median SMAPE values, outperforming all other models. A similar pattern emerges across other performance indicators (Appendix A.2), with TiRex demonstrating a strong ability to capture long-range epidemic dynamics, particularly in terms of RMSE and MAE, while Chronos SMALL and TimeGPT achieve the best results for MASE. In the medium-term horizon, TimeGPT delivers the most accurate forecasts across all metrics, whereas TiRex and Chronos variants show notable performance in short-term forecasting. Despite the superior performance of most of the foundation models, the Lag-Llama architecture exhibits greater dispersion and higher median error values, reflecting an architectural design that is less suited to capture temporal dependencies of epidemic incidence data. In comparison, the self-attention mechanism of TimeGPT and the stacked xLSTM blocks of TiRex enable these models to more effectively learn and predict the complex temporal patterns inherent in epidemic incidence cases. Overall, our empirical evaluation demonstrates that, while statistical and deep learning baselines remain competitive in certain horizons, the architectural innovations of the pre-trained TimeGPT and TiRex models make them especially valuable for policymakers, as they offer robust real-world epidemic forecasts that enable the design of effective intervention strategies.

4 Conclusion

In this study, we evaluate pre-trained foundation models for forecasting real-world epidemic incidence, comparing LLM-based architectures with statistical and machine learning approaches in capturing complex epidemic dynamics. Extensive empirical results demonstrate the superior performance of the attention-based TimeGPT framework and the xLSTM-based TiRex model in zero-shot forecasting of epidemic cases across multiple temporal horizons. Despite their strong modeling capabilities, LLM-based architectures struggle to accurately capture sudden disease outbreaks and peak incidence cases, highlighting a key limitation of time series foundation models. Future research will focus on addressing this challenge and extending the evaluation to spatiotemporal epidemic forecasting, assessing the potential of foundation models to capture both temporal and spatial dependencies in disease spread.

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A Appendix

A.1 Forecasting Performance Measures

Symmetric Mean Absolute Percentage Error (sMAPE): Provides percentage-based error normalization.

$$\frac{100\%}{h} \sum_{i=1}^{h} \frac{|y_i - \hat{y}_i|}{(|y_i| + |\hat{y}_i|)/2}$$

Root Mean Squared Error (RMSE): Sensitive to large errors; highlights deviations in magnitude.

$$\sqrt{\frac{1}{h} \sum_{i=1}^{h} (y_i - \hat{y}_i)^2}$$

Mean Absolute Error (MAE): Measures average absolute difference between predicted and actual values.

$$\frac{1}{h} \sum_{i=1}^{h} |y_i - \hat{y}_i|$$

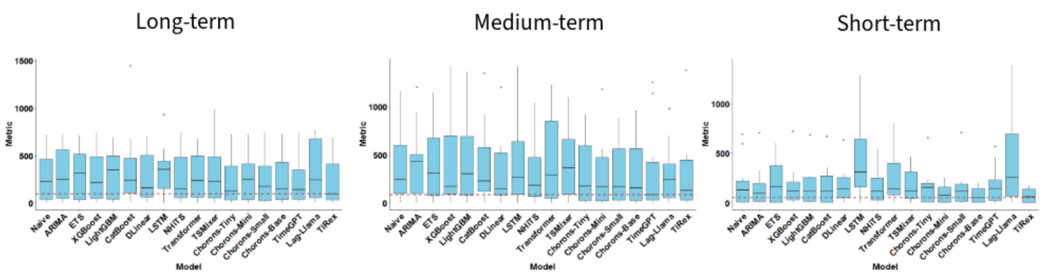
Mean Absolute Scaled Error (MASE): Allows comparison across datasets by scaling MAE with a naive forecast baseline.

$$\frac{\frac{1}{h} \sum_{t=1}^{h} |y_t - \hat{y}_t|}{\frac{1}{n-1} \sum_{t=2}^{n} |y_t - y_{t-1}|}$$

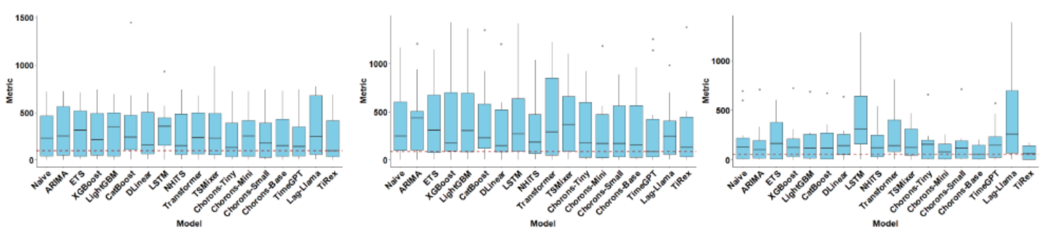
where h denotes the forecast horizon, $\hat{y_t}$ is the forecast corresponding to ground-truth observation y_t, and n represent the size of training observations.

A.2 Forecasting Performance Evaluation

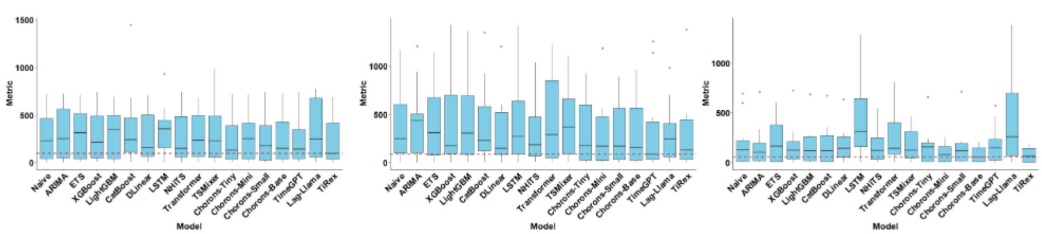
This section summarizes the performance of different foundation models and baseline architectures in forecasting the epidemic dynamics for long-term (Table 2), medium-term (Table 3), and short-term (Table 4) horizons. Furthermore, Fig. 2 visually depicts the median forecasting performance of different models across diverse accuracy measures.



(a) MAE



(b) MASE



(c) RMSE

Figure 2: Boxplots comparing the long-term (left panel), medium-term (middle panel), and short-term (right panel) forecasting performance of foundation models and baseline architectures in terms of (a) MAE, (b) MASE, and (c) RMSE metrics. In the plots, the dashed brown line corresponds to the lowest median value among all the models.

Table 2: Long-term forecasting performance comparison (best results are **highlighted**).

Metric	Models	Ahmed-abad Dengue	Bangkok Dengue	Columbia Dengue	Hong Kong Dengue	Singapore Dengue	Venezuela Dengue	Japan Influenza	Mexico Influenza	Australia Influenza	Venezuela Malaria	Colombia Malaria
MAE	Naive	12.41	451.11	717.55	3.62	234.41	640.64	228.66	33.14	54.01	222.40	480.13
	ARIMA	14.08	631.08	723.01	3.55	250.78	490.82	691.58	47.26	51.89	**188.63**	478.19
	ETS	12.75	313.60	710.48	6.61	131.54	485.55	376.69	29.71	51.89	701.29	548.80
	XGBoost	11.44	**213.83**	694.57	4.11	191.28	483.63	739.39	46.42	54.47	290.02	497.80
	LightGBM	11.61	413.54	692.51	3.56	350.47	518.35	685.25	31.70	51.95	245.67	481.14
	CatBoost	11.97	295.74	677.19	4.90	241.41	460.98	166.85	1445.30	52.19	219.03	483.96
	Dlinear	10.01	287.67	708.15	4.37	116.28	550.65	160.32	81.51	51.30	533.46	472.46
	LSTM	9.46	237.55	928.56	3.52	398.32	569.99	207.13	352.70	101.70	407.79	481.67
	NHiTS	10.60	352.85	741.66	4.32	130.15	526.09	149.69	32.13	87.20	487.24	476.28
	Transformer	11.53	265.62	**674.71**	3.69	237.36	643.66	511.71	56.30	69.07	209.17	482.19
	TSMixer	12.69	301.67	981.99	4.23	120.32	509.41	472.58	38.47	68.60	229.00	509.73
	Chronos TINY	10.47	278.52	721.84	4.69	132.63	425.47	54.96	28.13	45.64	348.15	464.08
	Chronos MINI	6.14	277.89	720.51	3.30	250.68	457.06	52.09	30.01	50.03	370.09	463.17
	Chronos SMALL	7.55	363.72	741.90	3.87	174.54	513.95	**47.55**	**21.88**	35.53	334.61	415.01
	Chronos BASE	8.08	416.86	724.24	3.39	151.15	555.54	57.09	31.12	49.57	379.60	442.55
	TimeGPT	**4.52**	237.23	742.04	3.92	143.28	**393.37**	78.87	55.20	**28.41**	308.07	486.13
	Lag-Llama	12.69	361.03	771.21	5.40	243.01	747.08	239.71	42.54	78.11	692.52	657.49
	TiRex	5.28	271.12	687.91	**2.82**	**96.14**	481.70	54.94	31.10	41.53	501.69	**350.94**
MASE	Naive	2.07	2.28	4.51	0.86	5.45	4.62	5.52	2.35	3.38	1.34	2.76
	ARIMA	2.33	3.24	4.55	0.80	5.83	3.52	17.74	3.35	3.22	**1.14**	2.75
	ETS	2.12	1.59	4.47	1.57	3.06	3.50	9.11	2.11	3.25	4.22	3.15
	XGBoost	1.89	**1.10**	4.37	0.93	4.45	3.47	18.97	3.30	3.38	1.75	2.86
	LightGBM	1.92	2.12	4.36	0.80	8.15	3.71	17.58	2.25	3.22	1.48	2.76
	CatBoost	1.98	1.52	4.26	1.11	5.62	3.30	4.28	102.62	3.24	1.32	2.78
	Dlinear	1.67	1.46	4.46	1.04	2.70	3.97	3.88	5.79	3.21	3.21	2.71
	LSTM	1.56	1.22	5.84	0.80	9.27	4.08	5.31	25.04	6.31	2.46	2.77
	NHiTS	1.77	1.79	4.67	1.03	3.03	3.80	3.62	2.28	5.46	2.93	2.74
	Transformer	1.91	1.36	**4.26**	0.83	5.64	4.61	13.13	3.96	4.29	1.25	2.75
	TSMixer	2.12	1.53	6.18	1.01	2.80	3.67	11.43	2.73	4.30	1.38	2.93
	Chronos TINY	1.73	1.43	4.54	1.06	3.08	3.05	1.41	2.00	2.83	2.10	2.67
	Chronos MINI	1.01	1.43	4.53	0.75	5.83	3.28	1.34	2.13	3.10	2.23	2.66
	Chronos SMALL	1.25	1.87	4.67	0.88	4.06	3.68	**1.22**	**1.55**	2.20	2.01	2.38
	Chronos BASE	1.34	2.14	4.56	0.77	3.52	3.98	1.46	2.21	3.08	2.29	2.54
	TimeGPT	**0.75**	1.22	4.68	0.89	3.41	**2.82**	2.02	3.88	**1.76**	1.84	2.77
	Lag Llama	2.10	1.85	4.87	1.22	5.78	5.35	6.15	2.99	4.85	4.13	3.75
	TiRex	0.87	1.39	4.34	**0.64**	**2.29**	3.45	1.41	2.19	2.58	3.00	**2.00**
RMSE	Naive	18.72	598.58	810.53	5.63	251.95	797.09	296.87	46.70	91.27	265.13	590.97
	ARIMA	20.02	729.38	818.73	4.73	269.00	646.86	716.72	52.97	87.06	**233.41**	603.11
	ETS	19.01	386.17	811.82	8.02	186.05	586.13	401.79	48.01	89.03	772.10	668.00
	XGBoost	17.39	**270.46**	777.96	5.43	210.10	610.74	764.92	69.75	91.99	349.30	658.21
	LightGBM	17.35	488.38	774.89	4.60	376.75	678.87	712.46	54.97	88.14	307.37	601.97
	CatBoost	18.36	351.42	766.73	5.73	259.65	602.09	236.27	1637.82	85.15	264.33	614.80
	Dlinear	14.81	341.36	818.34	5.78	155.79	697.21	185.06	89.21	87.22	598.11	611.95
	LSTM	14.07	336.71	1077.57	4.56	428.64	743.90	264.72	370.60	129.82	495.95	610.38
	NHiTS	16.34	407.97	843.85	4.97	168.41	629.80	166.65	46.06	119.29	535.83	596.75
	Transformer	17.51	311.55	**759.01**	5.01	311.91	809.14	533.85	61.00	102.84	259.34	575.28
	TSMixer	18.98	362.38	1282.62	5.62	149.81	652.15	497.74	46.79	102.45	288.18	610.46
	Chronos TINY	16.19	325.20	885.36	6.13	176.93	547.27	96.98	**37.99**	74.20	424.47	605.99
	Chronos MINI	8.96	322.50	801.20	4.33	271.01	554.34	93.73	50.90	84.46	461.34	552.70
	Chronos SMALL	12.08	459.74	860.86	5.12	195.60	644.07	**91.27**	39.46	57.42	420.01	535.59
	Chronos BASE	12.52	512.20	901.74	5.03	187.26	699.51	110.51	53.10	79.63	459.08	565.51
	TimeGPT	**6.58**	338.25	836.23	4.37	176.59	**484.36**	116.88	96.25	**48.62**	364.31	591.22
	Lag-Llama	16.85	451.80	873.60	6.28	297.73	974.60	299.94	61.62	108.69	863.45	824.37
	TiRex	8.08	339.27	779.92	**3.78**	**145.97**	643.63	102.21	52.88	62.65	565.71	**466.11**
SMAPE	Naive	141.27	83.45	38.08	38.38	66.54	56.10	139.04	86.83	80.02	15.26	30.78
	ARIMA	200.00	70.64	38.40	37.53	69.33	38.91	158.56	102.19	73.62	**13.07**	30.60
	ETS	150.80	49.00	37.70	91.20	56.57	38.81	144.20	78.87	72.40	63.95	33.52
	XGBoost	105.25	**31.63**	36.81	43.61	58.47	39.04	160.02	75.85	79.11	19.07	31.99
	LightGBM	103.26	54.60	36.67	38.14	83.08	41.72	158.13	87.58	72.78	16.52	30.83
	CatBoost	104.98	43.31	35.87	48.00	67.80	36.09	123.02	172.54	75.94	15.42	30.99
	Dlinear	92.28	46.96	37.55	48.29	39.78	45.73	130.07	118.24	72.08	44.22	30.17
	LSTM	82.67	32.56	55.58	37.62	87.59	47.25	142.15	194.08	191.98	32.11	30.84
	NHiTS	95.34	58.76	38.45	44.56	43.61	41.29	125.70	85.39	165.12	39.04	30.47
	Transformer	100.19	44.97	**35.64**	39.10	58.26	56.05	152.48	108.30	186.38	14.37	30.84
	TSMixer	145.37	48.59	43.43	46.31	40.97	41.27	149.07	94.33	187.05	15.54	31.87
	Chronos TINY	93.95	46.85	37.80	60.61	52.17	32.98	70.48	77.72	78.63	26.32	29.58
	Chronos MINI	61.61	45.33	38.24	38.92	69.12	35.51	59.46	95.78	70.16	28.42	29.66
	Chronos SMALL	67.56	58.37	39.50	47.21	54.85	40.43	**58.09**	**61.66**	57.13	25.21	26.34
	Chronos BASE	71.73	71.20	37.70	36.01	59.46	46.48	58.27	97.97	86.44	29.11	28.24
	TimeGPT	55.17	32.16	39.59	41.20	46.70	**30.46**	106.38	87.35	**43.13**	20.05	30.98
	Lag-Llama	95.92	60.65	40.11	89.72	138.53	71.65	190.77	159.84	173.34	59.41	46.77
	TiRex	**52.87**	40.84	36.44	**29.95**	**36.63**	37.95	67.14	86.32	92.30	41.08	**21.99**

Table 3: Medium-term forecasting performance comparison (best results are **highlighted**).

Metric	Models	Ahmedabad Dengue	Bangkok Dengue	Columbia Dengue	Hong Kong Dengue	Singapore Dengue	Venezuela Dengue	Japan Influenza	Mexico Influenza	Australia Influenza	Venezuela Malaria	Colombia Malaria
MAE	Naive	17.52	535.20	1163.91	3.45	163.93	667.53	249.04	138.30	58.44	299.69	869.55
	ARIMA	15.41	563.71	1204.17	3.22	161.37	444.54	447.56	150.87	51.11	435.03	937.16
	ETS	18.46	318.41	1143.21	5.12	195.12	588.57	308.45	92.24	62.50	759.04	840.02
	XGBoost	13.19	399.49	1423.67	3.35	172.16	750.28	164.33	118.30	69.54	652.70	1061.73
	LightGBM	14.94	305.42	1359.13	3.71	172.92	434.28	728.23	112.14	55.50	655.95	835.34
	CatBoost	12.53	**234.09**	1346.48	3.79	187.46	516.28	228.82	194.30	57.21	644.68	921.82
	Dlinear	16.91	392.06	1201.21	3.49	142.84	458.42	147.12	115.38	49.03	579.39	595.13
	LSTM	7.21	272.24	**795.86**	3.29	122.04	1414.21	210.44	989.88	60.12	292.19	479.12
	NHiTS	20.81	243.31	1037.64	3.55	184.87	561.63	160.73	79.58	58.34	556.50	386.22
	Transformer	15.10	463.61	920.49	3.19	271.83	1220.96	988.21	36.14	66.57	776.37	288.03
	TSMixer	16.75	368.71	1099.26	3.71	271.91	693.84	432.15	101.57	78.63	728.94	621.19
	Chronos TINY	13.10	503.81	920.57	4.36	178.06	438.34	40.09	13.37	39.00	721.93	689.83
	Chronos MINI	14.31	523.03	1180.25	2.84	194.66	**422.73**	**33.16**	16.66	50.41	561.83	**171.21**
	Chronos SMALL	14.29	596.11	885.13	2.89	168.78	526.81	35.62	31.71	30.60	649.77	436.54
	Chronos BASE	15.44	520.77	959.48	2.73	157.86	475.02	52.16	**4.94**	43.46	607.08	650.62
	TimeGPT	**6.94**	381.70	1252.99	**2.58**	**88.82**	466.57	43.54	58.90	**22.68**	269.13	1138.30
	Lag-Llama	21.99	701.47	981.68	5.44	340.21	450.01	244.49	41.27	73.35	**228.56**	358.98
	TiRex	9.90	415.94	1374.11	3.00	133.42	435.11	90.47	24.00	36.47	505.56	453.96
MASE	Naive	1.82	2.07	10.71	0.91	4.64	3.91	6.14	20.53	3.60	1.77	7.64
	ARIMA	1.55	1.94	11.08	0.85	4.57	3.04	11.68	24.07	3.13	2.50	8.23
	ETS	1.92	1.23	10.52	1.35	5.53	3.44	7.60	13.69	3.85	4.49	7.38
	XGBoost	1.32	1.38	13.09	0.88	4.88	5.13	4.29	18.87	4.26	3.75	9.33
	LightGBM	1.50	1.05	12.50	0.98	4.90	2.97	19.01	17.89	3.40	3.77	7.34
	CatBoost	1.26	**0.81**	12.39	1.00	5.31	3.53	5.97	31.00	3.50	3.70	8.10
	Dlinear	1.75	1.52	11.05	0.92	4.05	**2.68**	3.63	17.12	3.02	3.43	5.23
	LSTM	1.19	1.40	**5.01**	0.74	2.84	10.13	5.40	70.28	3.73	1.76	2.75
	NHiTS	2.16	0.94	9.54	0.93	5.24	3.29	3.96	11.81	3.60	3.29	3.39
	Transformer	1.52	1.96	8.93	0.84	7.69	8.34	25.79	5.77	4.08	4.46	2.73
	TSMixer	1.74	1.42	10.11	0.98	7.70	4.06	10.65	15.07	4.85	4.31	5.46
	Chronos TINY	1.32	1.73	8.47	1.15	5.04	3.00	1.05	2.13	2.39	4.14	6.06
	Chronos MINI	1.44	1.80	10.86	0.75	5.51	2.89	**0.87**	2.66	3.09	3.23	**1.50**
	Chronos SMALL	1.44	2.05	8.14	0.76	4.78	3.60	0.93	5.06	1.87	3.73	3.83
	Chronos BASE	1.55	1.79	8.83	0.72	4.47	3.25	1.36	**0.79**	2.66	3.49	5.72
	TimeGPT	**0.70**	1.31	12.16	**0.63**	**2.51**	3.19	1.14	9.40	**1.39**	1.55	10.80
	Lag-Llama	2.21	2.41	9.52	1.32	9.62	3.08	6.38	6.58	4.49	**1.31**	3.41
	TiRex	0.99	1.43	13.33	0.73	3.77	2.97	2.36	3.83	2.23	2.90	4.31
RMSE	Naive	21.45	670.79	1308.16	4.88	211.06	797.79	268.04	144.34	86.21	354.26	972.30
	ARIMA	18.86	635.33	1347.50	4.01	207.56	544.70	469.91	152.22	79.82	468.82	1033.67
	ETS	22.46	380.02	1270.22	6.57	240.67	661.74	325.32	95.22	89.10	817.09	929.68
	XGBoost	16.42	485.73	1558.67	4.66	216.08	892.18	212.15	121.15	94.65	682.56	1166.83
	LightGBM	17.75	330.75	1489.57	4.24	217.41	535.12	752.40	114.05	83.99	688.70	908.52
	CatBoost	15.14	316.61	1476.76	4.55	227.70	664.04	281.47	272.62	85.33	670.41	1013.31
	Dlinear	20.57	452.38	1341.94	4.39	187.99	512.80	155.93	119.03	77.11	626.41	662.53
	LSTM	10.75	351.13	**918.84**	4.13	172.99	1876.52	263.37	1078.43	97.42	353.68	601.72
	NHiTS	24.42	**295.74**	1172.35	4.12	229.33	765.22	172.59	82.36	85.93	609.84	438.82
	Transformer	17.95	543.17	977.27	3.91	304.69	1336.55	1002.87	37.42	92.16	807.85	370.38
	TSMixer	20.19	435.95	1235.03	4.63	310.87	791.60	457.02	104.36	101.22	788.66	683.26
	Chronos TINY	16.63	582.65	1041.84	5.95	219.26	557.55	86.41	23.75	62.64	758.38	751.26
	Chronos MINI	17.72	616.92	1335.83	4.44	237.65	560.88	90.53	19.90	74.11	598.34	**256.27**
	Chronos SMALL	17.91	692.33	1011.62	4.30	213.26	668.37	89.02	41.45	40.53	696.26	485.97
	Chronos BASE	19.14	616.73	1083.68	4.05	201.53	603.65	107.37	**6.09**	63.73	644.64	700.37
	TimeGPT	**8.58**	449.72	1442.08	**3.46**	**144.24**	**512.20**	**80.62**	61.48	**35.33**	309.65	1217.77
	Lag-Llama	26.24	798.74	1078.41	6.27	369.55	566.32	290.67	64.79	108.77	**271.15**	427.88
	TiRex	12.34	495.90	1484.55	3.82	193.15	566.87	174.38	25.74	46.97	548.25	494.05
SMAPE	Naive	104.41	74.81	60.57	41.88	77.66	49.48	145.02	158.25	110.27	21.04	52.54
	ARIMA	82.25	76.04	61.94	39.08	74.99	37.87	156.18	165.18	75.73	31.80	55.37
	ETS	111.52	42.56	60.13	74.15	102.62	46.56	146.95	148.04	134.46	65.03	51.57
	XGBoost	67.20	48.94	68.52	38.13	83.65	81.96	124.28	157.78	184.51	52.49	59.86
	LightGBM	78.34	39.05	66.72	42.59	84.11	36.98	165.91	156.70	91.28	52.77	51.46
	CatBoost	63.20	**27.54**	66.35	40.71	97.49	47.94	131.49	148.98	98.82	51.99	54.81
	Dlinear	97.57	54.24	61.87	42.76	62.49	38.99	133.09	154.11	73.31	45.47	40.72
	LSTM	68.26	40.02	**46.37**	35.24	48.50	61.61	133.66	188.77	104.55	19.19	30.67
	NHiTS	162.54	37.31	56.52	40.30	93.88	56.73	132.33	143.52	109.35	43.40	29.32
	Transformer	77.95	67.27	52.90	38.62	188.05	73.20	173.00	117.75	158.34	65.87	23.83
	TSMixer	95.59	50.02	58.61	46.08	176.07	51.78	153.00	200.00	200.00	61.61	41.99
	Chronos TINY	65.88	65.24	52.38	58.54	89.08	37.60	63.27	60.27	69.37	59.83	45.06
	Chronos MINI	80.20	66.12	61.06	33.17	102.85	**35.44**	54.59	81.59	101.01	43.57	**15.39**
	Chronos SMALL	82.67	80.79	51.02	35.49	81.21	47.62	**51.81**	101.88	65.10	52.29	32.13
	Chronos BASE	88.76	65.96	53.81	31.65	73.74	41.15	53.56	**41.75**	72.95	47.86	43.37
	TimeGPT	**37.11**	47.47	63.39	**28.93**	**30.73**	39.66	76.44	135.73	**34.31**	18.33	63.51
	Lag-Llama	145.39	118.01	55.98	81.88	191.31	38.17	149.35	173.83	136.40	**15.34**	28.55
	TiRex	49.50	49.54	68.00	34.76	54.62	36.71	74.23	98.31	84.46	38.15	33.39

Table 4: Short-term forecasting performance comparison (best results are **highlighted**).

Metric	Models	Ahmed-abad Dengue	Bangkok Dengue	Columbia Dengue	Hong Kong Dengue	Singapore Dengue	Venezuela Dengue	Japan Influenza	Mexico Influenza	Australia Influenza	Venezuela Malaria	Colombia Malaria
MAE	Naive	18.80	599.00	245.57	5.60	132.72	693.73	**4.43**	3.89	67.14	141.67	199.93
	ARIMA	19.64	333.43	195.64	5.18	126.48	707.25	15.20	4.09	65.23	101.18	193.79
	ETS	12.48	349.91	197.19	4.67	164.30	603.71	5.10	3.78	65.14	513.78	403.04
	XGBoost	4.34	310.22	212.17	2.14	123.97	723.93	212.85	6.64	57.21	105.24	207.94
	LightGBM	17.85	270.20	272.56	2.48	116.28	685.76	16.88	**3.74**	69.25	156.03	249.80
	CatBoost	11.81	279.32	357.49	2.84	**115.28**	673.60	5.23	6.23	49.64	196.74	265.58
	Dlinear	12.07	278.84	235.34	1.86	140.71	634.70	98.66	46.97	56.18	293.70	205.79
	LSTM	6.95	269.94	741.26	3.60	313.14	625.35	659.01	1280.52	54.18	269.54	478.34
	NHiTS	12.82	210.06	260.90	2.82	120.57	541.66	113.65	18.89	43.16	520.63	243.11
	Transformer	7.31	546.33	468.22	3.56	118.00	811.33	342.06	74.78	90.72	143.21	185.05
	TSMixer	22.37	229.24	398.25	1.93	164.71	**432.88**	5.51	72.54	468.27	**91.77**	**124.44**
	Chronos TINY	6.52	206.92	195.97	2.40	173.81	658.50	16.78	6.78	52.32	157.52	241.10
	Chronos MINI	5.90	170.06	96.74	**1.41**	159.68	751.84	18.45	6.13	61.44	160.32	252.93
	Chronos SMALL	8.54	216.14	116.89	2.90	148.37	710.69	20.71	18.37	30.50	201.24	184.91
	Chronos BASE	7.50	205.50	**90.22**	1.80	149.52	696.67	10.67	4.37	20.06	144.92	166.78
	TimeGPT	8.28	250.00	462.80	2.02	155.06	569.66	33.11	18.74	31.08	145.58	215.90
	Lag-Llama	6.51	245.92	1075.98	3.11	258.60	454.58	272.27	38.66	98.94	938.40	1382.67
	TiRex	**4.01**	**148.16**	109.13	2.04	164.76	651.61	5.72	3.76	**17.13**	116.88	175.58
MASE	Naive	3.02	2.21	2.52	2.24	3.29	4.72	**0.67**	0.68	2.63	1.18	1.71
	ARIMA	3.16	1.34	2.15	2.07	3.05	4.63	2.26	0.74	2.55	0.82	1.60
	ETS	2.01	1.29	2.02	1.87	4.08	4.11	0.77	**0.66**	2.55	4.27	3.44
	XGBoost	0.70	1.25	2.33	0.86	2.99	4.74	31.59	1.21	2.24	0.85	1.72
	LightGBM	2.87	1.09	2.99	0.99	2.81	4.49	2.51	0.68	2.71	1.27	2.06
	CatBoost	1.90	1.13	3.92	1.14	**2.78**	4.41	0.78	1.13	1.94	1.60	2.19
	Dlinear	1.94	1.03	2.41	0.74	3.49	4.32	14.95	8.23	2.20	2.44	1.76
	LSTM	1.15	1.39	4.66	0.81	7.28	4.48	16.91	90.92	3.36	1.62	2.75
	NHiTS	2.06	0.77	2.67	1.13	2.99	3.69	17.22	3.31	1.69	4.33	2.08
	Transformer	1.07	2.31	5.14	0.94	2.85	5.32	50.78	13.60	3.58	1.16	1.53
	TSMixer	3.59	0.84	4.08	0.77	4.09	**2.95**	0.83	12.71	18.33	**0.76**	**1.06**
	Chronos TINY	1.05	0.83	2.15	0.96	4.19	4.31	2.49	1.23	2.05	1.28	1.99
	Chronos MINI	0.95	0.69	1.06	**0.56**	3.85	4.93	2.74	1.12	2.40	1.30	2.09
	Chronos SMALL	1.37	0.87	1.28	1.16	3.58	4.66	3.07	3.34	1.19	1.63	1.53
	Chronos BASE	1.21	0.83	**0.99**	0.72	3.61	4.56	1.58	0.79	0.79	1.18	1.38
	TimeGPT	1.27	1.01	5.08	1.01	3.74	3.73	4.91	3.41	1.23	1.18	1.78
	Lag-Llama	1.00	0.99	11.81	1.56	6.24	2.98	40.42	7.03	3.90	7.62	11.41
	TiRex	**0.62**	**0.60**	1.20	1.02	3.98	4.27	0.85	0.68	**0.68**	0.95	1.45
RMSE	Naive	22.00	749.68	294.93	6.81	189.60	832.29	**7.15**	4.75	79.45	154.17	301.41
	ARIMA	21.95	377.79	254.08	5.85	189.92	832.98	15.98	4.91	74.20	116.93	301.62
	ETS	13.62	417.90	254.14	5.11	235.31	729.76	8.05	4.45	75.02	553.28	523.88
	XGBoost	5.24	349.45	263.80	2.63	173.85	852.81	301.99	7.76	73.77	128.53	305.66
	LightGBM	20.64	283.19	317.01	2.78	161.72	815.52	18.83	**4.37**	89.94	177.77	361.47
	CatBoost	13.08	327.63	402.01	3.68	161.36	801.70	8.15	7.41	67.49	219.78	369.14
	Dlinear	13.21	333.91	288.91	2.06	207.56	767.50	105.34	50.59	68.94	328.49	316.20
	LSTM	10.73	321.78	853.67	4.45	332.40	806.32	740.13	1390.83	91.94	328.46	600.28
	NHiTS	14.03	248.27	315.69	3.37	180.04	665.83	129.89	20.12	55.39	555.05	359.68
	Transformer	8.57	676.69	591.03	4.22	**139.25**	937.15	419.26	74.90	115.15	170.81	290.41
	TSMixer	25.01	286.31	467.52	2.31	236.92	**514.66**	8.48	72.97	518.08	**116.13**	**174.44**
	Chronos TINY	8.74	213.09	299.40	2.70	237.26	776.51	34.71	9.93	69.64	190.43	319.43
	Chronos MINI	7.81	209.92	170.63	**1.71**	218.56	867.71	37.66	7.63	69.88	192.11	309.16
	Chronos SMALL	10.98	240.79	188.36	3.43	212.76	830.23	41.09	21.15	44.08	233.63	238.30
	Chronos BASE	9.61	216.11	**158.89**	2.19	213.59	809.89	18.37	5.89	28.71	165.97	219.00
	TimeGPT	9.30	284.65	530.30	2.33	211.21	700.20	52.85	22.77	39.22	175.78	330.21
	Lag-Llama	8.99	274.75	1111.88	3.58	321.06	554.65	299.43	48.56	120.49	1200.35	1474.33
	TiRex	**5.06**	**166.61**	181.06	2.27	235.37	769.96	8.92	5.04	**25.59**	131.16	224.76
SMAPE	Naive	87.65	70.11	23.67	50.79	37.29	67.78	**64.36**	46.04	71.35	8.56	22.37
	ARIMA	90.86	27.05	19.91	48.98	33.68	67.00	115.51	47.29	68.82	6.30	22.23
	ETS	76.08	27.01	19.79	68.93	50.11	55.53	81.18	44.33	68.26	38.21	36.54
	XGBoost	48.97	27.07	21.29	25.19	32.95	69.39	153.41	93.56	109.49	6.57	23.46
	LightGBM	86.62	23.67	26.14	27.97	30.63	63.95	118.66	42.75	127.89	9.84	26.57
	CatBoost	74.71	25.00	32.31	31.68	**30.26**	62.35	86.27	84.01	51.08	12.58	27.87
	Dlinear	74.85	25.02	22.88	22.29	40.03	59.42	174.38	140.88	64.72	19.83	22.76
	LSTM	64.56	41.72	38.23	37.83	78.62	54.09	177.71	193.34	77.95	19.45	30.62
	NHiTS	76.87	17.74	24.85	36.13	32.53	47.72	200.00	103.32	55.47	38.63	25.56
	Transformer	56.77	80.97	38.15	41.99	31.69	82.30	188.16	159.91	74.69	9.05	21.52
	TSMixer	95.28	20.14	34.46	22.86	50.22	36.84	93.88	200.00	127.71	**5.71**	**15.80**
	Chronos TINY	**41.79**	18.27	19.48	27.57	53.38	60.73	76.21	59.84	58.07	9.98	27.07
	Chronos MINI	46.32	14.29	11.20	**16.21**	47.43	73.69	85.79	52.16	67.21	10.15	29.18
	Chronos SMALL	60.82	17.69	13.06	29.43	42.25	67.71	83.72	95.00	41.22	13.11	22.16
	Chronos BASE	52.06	17.82	**10.56**	20.57	42.71	66.01	88.41	46.59	24.16	9.11	20.04
	TimeGPT	65.97	20.99	39.03	24.55	45.73	49.18	116.42	93.51	39.96	9.17	23.92
	Lag-Llama	52.88	24.98	71.62	46.91	100.68	**33.31**	187.69	131.33	130.80	76.59	83.03
	TiRex	41.88	**12.77**	12.33	25.44	48.99	59.74	71.63	**41.25**	**23.06**	7.27	21.18