CLIMATE CHANGE ANALYSIS USING EARTH'S SURFACE TEMPERATURE: HIERARCHICAL TIME SERIES

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***Abstract*— The concept of climate change encompasses the profound impacts of global warming on Earth's weather systems, with contemporary changes far exceeding historical variations and predominantly driven by human-induced factors such as elevated levels of atmospheric greenhouse gases from activities like fossil fuel combustion and agriculture. Efforts by organizations like the United Nations are actively combating these changes. Within Earth's climatic framework, land surface temperature plays a pivotal role, influencing crucial processes like energy and water exchange between the surface and atmosphere, thereby affecting vegetation growth patterns. Accurate comprehension of global and regional land surface temperatures, coupled with factors like vegetation and soil moisture, aids in evaluating land surface-atmosphere interactions and serves as a valuable metric for surface conditions.**

This paper employs hierarchical time series forecasting to analyse and project land surface temperatures for major cities across countries. Hierarchical forecasting is essential when dealing with time series data aggregated hierarchically, ensuring a coherent approach to forecasting across different levels of granularity. By employing hierarchical time series forecasting, this research addresses the challenge of aggregating data to specific levels, ensuring consistency in temperature projections from city to country levels.

***Keywords*—Time series prediction; Earth surface temperature; Climate change.**

1. Introduction

1.1 Background

Climate change, identified as the foremost health threat by the World Health Organization and health experts globally, necessitates urgent action to limit global temperature rise to 1.5°C, as emphasized by the IPCC and various studies [1], [2], [3]. Despite the inevitability of some temperature increase due to past emissions, each tenth of a degree rise poses considerable risks to human health and well-being [4]. The correlation between economic growth and global warming is evident, with a notable increase in global temperatures mirroring the rise in global GDP from 1960 to 2019 [5]. Human-induced warming has already escalated by 1.0°C since pre-industrial times, with projections indicating a potential 1.5°C increase between 2030 and 2050 [3]. Addressing this challenge demands substantial reductions in carbon dioxide emissions by 2030 to avert surpassing the critical 1.5°C threshold. Understanding and forecasting land surface temperatures in major cities of 85 countries using hierarchical time series forecasting are crucial steps towards raising awareness of the imminent impacts of rising temperatures on health and ecosystems.

1.2 Literature Review and Research Objective

The global average temperature, a pivotal metric in climate research, provides crucial insights into Earth's energy balance dynamics despite its diverse temperature patterns. In [6], Lean and Rind's model predicts a notable temperature increase over the next two decades, emphasizing the complex interplay of natural and human influences on climate evolution. Observations post-1970 highlight a significant warming trend influenced by factors like greenhouse gas concentrations and volcanic activity, underscoring the dominant role of anthropogenic forces in driving long-term temperature shifts. Advances in satellite data analysis by Dash et al [7] and the development of high-resolution climate data by Karger et al. [8] further enhance our understanding of climate dynamics, emphasizing the need for continuous monitoring and predictive modeling in climate research.

The escalating global temperatures, primarily driven by human activities, have intensified the greenhouse effect, leading to a surge in greenhouse gas emissions and a range of climate-related impacts. In [4], an IPCC reports highlight the consequences of climate change on ecosystems and human life, necessitating urgent collective action to mitigate these effects. Recent research underscores the significant changes in Earth's heat content attributed to human-induced greenhouse gases, emphasizing the need for further investigation into factors influencing the Earth's climate system. Time series forecasting, crucial for strategic decision-making, continues to evolve with a focus on hierarchical time series forecasting techniques to ensure coherent and reliable predictions across complex hierarchical structures.

The field of time series forecasting has witnessed significant progress over the past 25 years, with advancements in statistical methodologies and models. However, unresolved challenges persist, necessitating further exploration in areas such as multivariate techniques, nonlinear models, and robust statistical methodologies. Recent developments in non-Gaussian forecasting and prediction methods for discrete sample spaces present promising avenues for future research, driven by the availability of large datasets and advanced computational tools like neural networks. The synthesis of climate research and time series forecasting underscores the critical need for ongoing innovation and collaboration to address the complex challenges posed by climate change and to enhance predictive capabilities for informed decision-making.

Many researchers scrutinize diverse time series forecasting techniques, comparing their efficacy across various domains. The authors of [9] investigate short, medium, and long-term forecasting methodologies, emphasizing the importance of understanding data characteristics and objectives for optimizing forecasting outcomes. Garima and Bhawna in [10] compare ARIMA and ETS models for weather forecasting, showcasing their application in predicting meteorological parameters and evaluating forecast precision. In [11], Chen et al. utilize SARIMA techniques to forecast monthly mean temperatures in Nanjing, achieving accurate predictions based on historical data analysis. Cerqueira et al. challenge the notion that machine learning surpasses traditional statistical methods in time series forecasting [12], emphasizing the nuanced relationship between sample size, model performance, and forecasting accuracy. These studies collectively enrich our understanding of time series forecasting methodologies across different applications and disciplines.

In the domain of climate analysis and forecasting, several studies delve into time series data intricacies, focusing on variables like temperature and precipitation. In [13], the authors scrutinize temperature and precipitation fluctuations in the Bhagirathi river basin using seasonal ARIMA, highlighting the efficacy of SARIMA models in predicting weather patterns. In [14], Papacharalampous et al. explore automated forecasting algorithms for monthly temperature and precipitation data, emphasizing the competitive forecasting capabilities of models like Prophet. Nury et al. underscore the utility of ARIMA models in predicting regional temperatures for environmental planning [15]. Yuchuan and David [16] develop an ARIMA-based method for short-term temperature and precipitation trends, enhancing climate-aware decision-making. These studies collectively contribute to advancing our comprehension of climate dynamics and aiding informed decision-making amidst environmental changes.

Hierarchical time series forecasting, organizing multiple time series into levels based on categories, presents challenges and opportunities for forecasting methods. Hyndman et al. propose a superior hierarchical forecasting approach that forecasts each series at every hierarchy level, reconciling forecasts using a regression model for accurate predictions aligning with the hierarchical structure [17]. In [18] and [19], subsequent works by Hyndman and colleagues enhance computational efficiency and covariance estimation for improved forecast reconciliation, underlining the significance of hierarchical time series forecasting in addressing complex challenges, notably in understanding and predicting climate change impacts on urban environments. These advancements emphasize the practicality and efficacy of hierarchical forecasting in handling intricate real-world forecasting tasks.

The research projects discussed have largely overlooked hierarchical time series benefits, with only a few studies mentioning this approach. Our study uniquely explores all aspects of hierarchical time series models, crucial due to Earth's warming trend driven by human-induced greenhouse gas emissions. Urban areas, with their heat island effect and high population density, are particularly vulnerable to climate change impacts, yet many remain indifferent. Our study aims to forecast land surface temperatures in major cities globally to understand future implications, filling a gap in hierarchical time series forecasting often missed in existing research.

Details of the proposed methodology are introduced in Section 2. Results are evaluated and discussed in Section 3. Section 4 concludes the work.

2. Methodology Framework

Fig. 1 represents the methodology framework proposed in this paper. The methodology used entails crucial steps like selecting the target data, pre-processing the selected data, converting the data into a structured and understandable format, exploratory data analysis, creating a hierarchy, selecting a model and revision method, implementing hierarchical time series forecasting, and assessing the forecast's performance using evaluation measures.

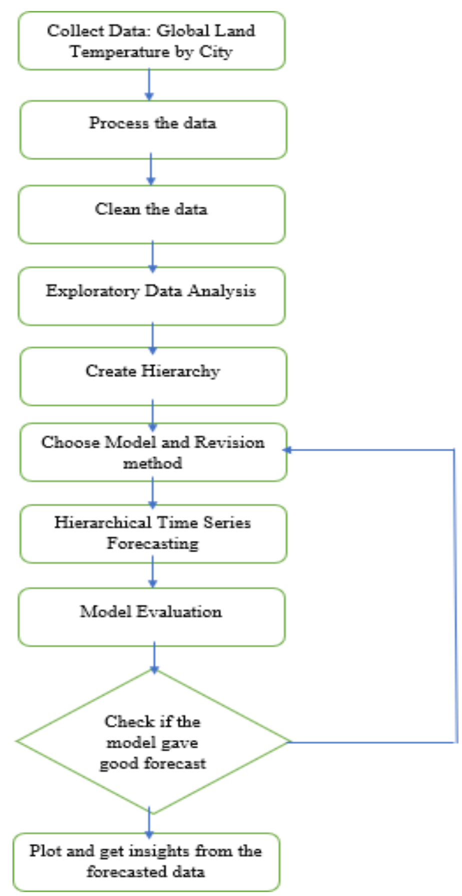


Fig.1. Flowchart of proposed research methodology

2.1. Data Description

The Lawrence Berkeley National Laboratory affiliate Berkeley Earth, initially known as the Berkeley Earth Surface Temperature project, was founded in early 2010 to address concerns surrounding global warming and the instrumental temperature record. Utilizing preliminary results and datasets from Berkeley Earth, available on platforms like Kaggle, our study delved into the analysis of terrestrial temperature data for climatological research. The dataset examined encompassed monthly average land surface temperatures of major cities in 159 countries worldwide from 1743 to 2013, providing a comprehensive geographical breakdown by country and city, complete with longitude and latitude coordinates. Data preprocessing was essential due to null values within the dataset, following which exploratory data analysis techniques were employed to extract valuable insights.

By leveraging the rich dataset sourced from Berkeley Earth, our investigation aimed to contribute to the understanding of global temperature trends and patterns. The data's temporal and geographical scope offered a unique opportunity to explore long-term temperature variations across major cities, facilitating a deeper comprehension of climatic dynamics at both local and global scales. Through meticulous data cleaning and exploratory analysis, our study sought to unveil hidden trends and correlations within the dataset, ultimately enhancing our knowledge of terrestrial temperature variations and their implications for climate research and policy-making.

2.2. **Hierarchical Time Series**

In hierarchical time series forecasting, data is collected or aggregated at multiple levels in a hierarchical structure, necessitating the need for coherent forecasts across these levels. Unlike traditional time series forecasting methods like ARIMA, ETS, or Prophet, hierarchical time series forecasting does not represent a standalone forecasting technique. Instead, it focuses on ensuring consistency in forecasts across different levels of a hierarchy of time series data using diverse methodologies. This study employs hierarchical time series forecasting to derive country-level average temperature data and ensure alignment between projections at the city level and those at the country level.

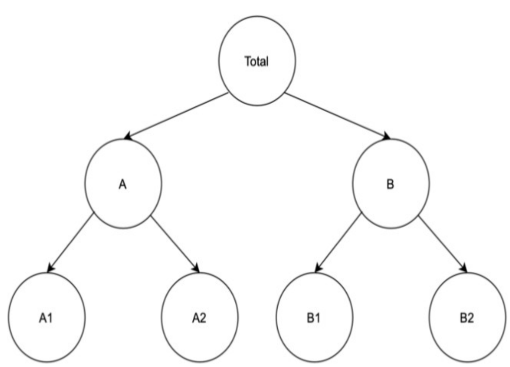


Fig. 2. Hierarchical time series

By maintaining coherence in forecasts within the hierarchical structure, this approach enhances the accuracy and reliability of temperature predictions, contributing to a more comprehensive understanding of temperature trends at varying spatial scales.

2.2.1 Forecasting Methods

In the context of hierarchical time series forecasting, four common methodologies are typically employed:

1. Bottom-Up Approach:

In the bottom-up method, forecasts are generated at the lowest level of the hierarchy. These forecasts are then aggregated to obtain estimates for higher levels within the hierarchy.

2. Top-Down Approach:

The top-down strategy involves forecasting at the highest level of the hierarchy first. Subsequently, these forecasts are disaggregated to obtain predictions for the lower levels of the hierarchy.

3. Middle-Out Approach:

The middle-out approach combines elements of both the bottom-up and top-down methods, specifically applicable to strictly hierarchical time series. Forecasting is directly performed at the middle level of the hierarchy. The bottom-up method is then utilized to aggregate forecasts for all levels above the chosen middle level, while the top-down method is applied to forecast the levels below the middle level.

4. Optimal Reconciliation Approach:

The optimal reconciliation approach assumes that base forecasts for all series at all levels approximately adhere to the hierarchical structure. A linear regression model is used to reconcile individual forecasts, ensuring coherence across the hierarchy. Basic forecasts from all levels are combined by solving a set of equations to determine appropriate weights, preserving the hierarchical relationships between different levels.

Each of these methods has its own characteristics and potential biases towards the levels being forecasted. Through testing all these approaches, evaluating their performance, and selecting the most suitable method based on the specific forecasting requirements, we can obtain accurate and reliable forecasts that effectively address the issues at hand.

2.2.2 Creating the Hierarchy

In hierarchical time series forecasting, a key aspect is establishing a structured hierarchical representation. A common method is to use a dictionary to create a hierarchical tree. Nodes are keys in the dictionary, with their children as corresponding values. This recursive structure allows for nested levels of children. This approach simplifies the organization of hierarchical relationships, aiding in accurate predictions across different levels of the hierarchy.

2.2.3 Model and Revision Methods

The model selection and revision method play crucial roles in determining forecasting accuracy. In this study, the model choice dictates the type of model used for individual time series forecasting, while the revision method outlines the approach to hierarchical forecasting. The "scikit-hts" package, known for its proficiency in modeling hierarchical time series, was pivotal in this research, offering the 'HTSRegressor' class. Various models, including Auto ARIMA, SARIMAX, Holt-Winters exponential smoothing, and Facebook's Prophet, were employed. Additionally, revision techniques such as the Bottom-Up (BU) approach, Average Historical Proportions (AHP) for top-down forecasting, and the Optimal Combination using Ordinary Least Squares (OLS) were utilized. Through a comparative analysis of different model and revision method combinations, the most effective approach for addressing the research problem was identified.

2.2.4 Model Evaluation Using RMSE

In evaluating the forecasting model, the HTS regressor model predicts data from the beginning of the historical dataset, eliminating the need for a train-test split. The assessment of model performance is conducted using Root Mean Square Error (RMSE), a metric that quantifies the differences between actual and predicted values. RMSE calculates the square root of the mean of the squared differences between observed and predicted values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left\| y(i) - \widehat{y(i)} \right\|^2}{N}}$$

where N is the number of data points, y(i) is the i-th measurement, and $\hat{y}$(i) is its corresponding prediction.
This metric provides insights into the accuracy and effectiveness of the forecasting model, measuring discrepancies between true and predicted values for each data point.

By utilizing RMSE as the evaluation metric, the forecasting model's performance can be effectively assessed and compared across different model and revision method combinations.

3. Results and Discussion

Following the execution of forecasting models, the subsequent step involves evaluating and selecting the model that delivers the most precise predictions with minimal margin for error. Utilizing tools like Auto Arima, SARIMAX, Prophet, and Holt-Winters, the forecasting process incorporates both bottom-up and top-down approaches, alongside optimal combinations and reconciliation techniques. Evaluation criteria include Root Mean Square Error (RMSE) and an assessment of projected data points up to 2050. In this scenario, a train-test split is unnecessary as the HTS regressor model forecasts data from the historical dataset's inception, utilizing actual and predicted historical data from 1894 to 2012 for model assessment via RMSE. RMSE, a vital metric in model evaluation, gauges deviations from actual values by averaging errors; a RMSE value of 0 shows that the model provides an accurate representation of the data, so smaller RMSE values indicate higher-quality models and more accurate predictions, while higher values imply substantial discrepancies between predictions and actual data, aiding in feature assessment for prediction model improvement.

3.1. **Model Evaluation**

3.1.1 Auto-Arima

The application of Auto-Arima automatically determines the optimal order for an ARIMA model. Through a structured process, the Auto-Arima function refines ARIMA parameters, initiates differencing tests, and investigates seasonal differentials, enhancing model accuracy. Leveraging various criteria like the Akaike Information Criterion, the model selects the ARIMA configuration that minimizes the criterion value, ensuring optimal performance.

The study presents a comprehensive evaluation of the auto ARIMA model's performance across different geographical scales. RMSE values, illustrated in Table 1, reveal the superiority of the bottom-up (BU) revision method, yielding an RMSE of 2.75 at the city level. However, discrepancies emerge at the national and global levels, indicating challenges in matching observed and projected temperatures accurately.

Model	RMSE_City	RMSE_Country	RMSE_Total
Arima AHP	48.014634	9426529	2396793000
Arima BU	2.757226	9301457	2350191000
Arima OLS	441.310239	363.70	1303.2

Table 1. Auto-Arima RMSE table

Fig. 3 contrasts the observed and projected global temperature values using BU, AHP, and OLS revision methods. Notably, forecasted global temperatures tend to overshoot observed values, indicating a lack of alignment. Similarly, Table 2 showcases elevated RMSE values at the country level, irrespective of the revision method employed. Although OLS displays comparatively lower RMSE values at the country level, discrepancies persist, suggesting suboptimal model fits.
In contrast, city-level RMSE values, as depicted in Table 1, outshine global and country-level counterparts. The BU and AHP methods demonstrate superior predictive accuracy compared to OLS, with the BU strategy yielding the most favorable results. Fig. 4 visualizes the discrepancy between observed and predicted nation-level temperatures, highlighting the BU method's superior predictive capabilities.

While the auto ARIMA model excels at city-level temperature predictions, challenges persist at broader geographical scales. The BU revision method emerges as the most effective strategy for city-level forecasts, offering superior accuracy and alignment with observed temperature data.

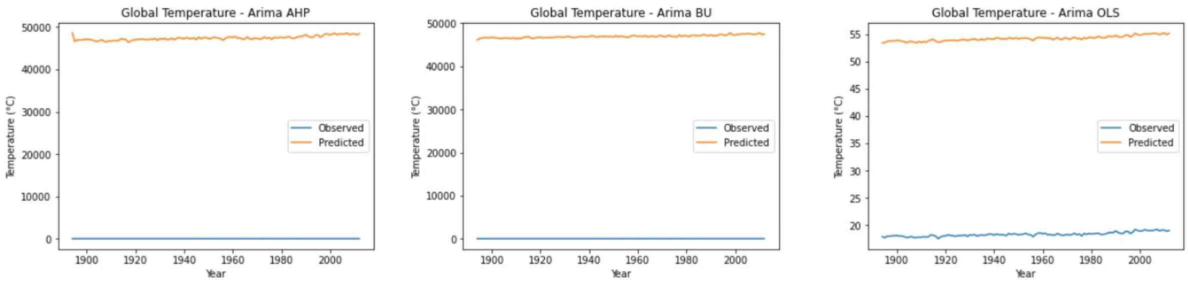


Fig. 3. Observed vs Predicted plot using Arima - Global temperature

Country	City	RMSE Arima AHP	RMSE Arima BU	RMSE Arima OLS
Bangladesh	Dhaka	18.339219	2.205497	632.94280
Bangladesh	Rajshahi	12.824577	2.326885	629.457691
Brazil	Rio De Janeiro	76.859878	1.468905	508.909871
Brazil	São Paulo	76.742661	1.707354	507.232933
China	Chongqing	10.136729	1.836640	260.911193
China	Shanghai	24.028938	2.393814	261.303495
Congo	Bukavu	39.819579	0.555325	553.968422
Congo	Kinshasa	66.662300	1.174492	554.429907
Egypt	Cairo	2.112856	1.529681	488.743064
Egypt	Luxor	1.728384	2.231606	488.403315
Ethiopia	Addis Abeba	32.755887	0.754461	404.929808
Ethiopia	Gondar	31.950737	1.320818	405.276084
France	Lyon	21.538990	3.616053	158.132935
France	Paris	10.762795	3.858453	158.554843
Germany	Berlin	25.351705	4.227415	130.135085
Germany	Hamburg	20.634497	3.066592	125.999137
India	Delhi	5.206420	4.072059	690.703270
India	Thiruvananthapuram	72.346067	0.982712	684.156830
Indonesia	Jakarta	65.691289	0.632009	691.675617
Indonesia	Makasar	63.877411	0.800036	691.668775
Iran	Tabriz	52.837950	3.693021	313.760341

Iran	Yazd	23.602300	2.199806	317.388443
Italy	Rome	15.127986	2.341251	214.830900
Italy	Venice	19.109275	2.526356	215.403125
Japan	Hiroshima	19.854573	2.238869	255.332325
Japan	Tokyo	28.140729	1.734219	255.452074
Mexico	Guadalajara	19.593213	0.814211	431.035604
Mexico	Mérida	43.047165	1.161973	430.697911
Nigeria	Kano	41.840856	2.793822	727.935988
Nigeria	Lagos	70.458690	0.820838	726.900738
Pakistan	Karachi	10.987886	2.100574	644.556084
Pakistan	Lahore	3.905321	3.780943	640.281816
Philippines	Davao	58.615814	0.645436	713.415456
Philippines	Manila	55.099935	1.273706	711.402487
Russia	Moscow	95.970812	6.913451	141.346383
Russia	Saint Petersburg	67.182898	6.766734	141.980943
South Africa	Cape Town	69.388952	1.000696	298.633797
Tanzania	Dar Es Salaam	89.726630	0.721565	506.479851
Thailand	Bangkok	54.194206	1.285081	709.687792
Turkey	Istanbul	11.824897	2.455631	237.685961
United Kingdom	London	7.501645	2.834723	115.509567
United Kingdom	Oxford	7.501645	2.834723	115.509567
United States	Chicago	38.736061	6.280253	272.637273
United States	New York	50.282877	3.060136	267.500238

Table 2. Auto-Arima RMSE table of city level temperature

3.1.2 SARIMAX

In this study, an advanced iteration of the ARIMA model, SARIMAX (Seasonal Auto-Regressive Integrated Moving Average with eXogenous components), was investigated, offering a seasonal equivalent model capable of incorporating external influences. SARIMAX comprises seven parameters, with the initial three mirroring those of ARIMA and the subsequent four delineating the seasonal pattern. Additional parameters encompass the season's length, seasonal outcomes despite a city-level RMSE of 14.52, relatively high when compared to the average RMSE. Fig. 4 visually represents differentiation, seasonal moving average, and seasonal autoregressive components. Notably, seasonal effects were not factored into the analysis, with default p, d, and q orders of 1, 0, and 0, respectively, employed in SARIMAX modeling.

The evaluation, showcased in Table 3, underscores that city-level RMSE values outperform national and global averages, with the bottom-up approach yielding the most favorable
the disparity between projected and observed global temperatures via SARIMAX, revealing significantly elevated

predicted values compared to actual readings, elucidating the model's struggle to accurately reflect global temperature trends. accentuates the divergence between actual and projected values, the BU approach stands out for its lower RMSE values, indicative of a well-fitted model. Moreover, Table 4 delineates city-level RMSE values, showcasing superior accuracy compared to national and global levels. While the OLS revision method exhibits higher RMSE actual and projected nation-level temperatures, revealing prediction variances among revision methods. Despite the BU method's low RMSE, potential overfitting concerns are highlighted, suggesting a need for further evaluation to mitigate such risks. These findings collectively underscore the challenges in accurately capturing temperature trends at different geographical scales using SARIMAX, emphasizing the importance of method selection and model fitting in temperature forecasting analyses.

Model	RMSE_City	RMSE_Country	RMSE_total
SARIMAX AHP	55.252	8724648.760	2178714837.688
SARIMAX BU	14.525	8584289.023	2135455268.622
SARIMAX OLS	408.973	343.689	1236.651

Table 3. SARIMAX RMSE table

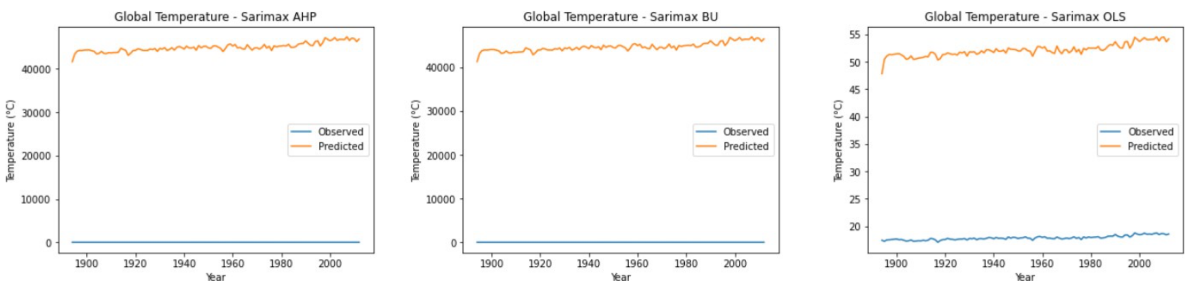


Fig. 4. Observed vs Predicted plot using SARIMAX - Global temperature

Country	City	RMSE SARIMAX AHP	RMSE SARIMAX BU	RMSE SARIMAX OLS
Bangladesh	Dhaka	29.795	6.780	616.860
Bangladesh	Rajshahi	26.076	8.142	619.136
Brazil	Rio De Janeiro	82.930	2.110	496.819
Brazil	São Paulo	73.146	3.164	496.952
China	Chongqing	18.346	16.458	242.151
China	Shanghai	29.994	21.970	257.613
Congo	Bukavu	39.228	0.532	541.754
Congo	Kinshasa	67.321	1.200	542.758
Egypt	Cairo	7.157	9.622	475.750
Egypt	Luxor	11.990	13.235	477.299
Ethiopia	Addis Abeba	36.256	0.969	392.718
Ethiopia	Gondar	37.050	1.342	393.384
France	Lyon	27.019	14.713	156.306
France	Paris	15.080	12.314	152.224
Germany	Berlin	31.364	17.399	125.961
Germany	Hamburg	25.460	14.158	123.547
India	Delhi	27.044	16.229	691.006
India	Thiruvananthapuram	79.169	1.255	661.489
Indonesia	Jakarta	68.437	0.597	678.199
Indonesia	Makasar	64.374	0.703	678.395
Iran	Tabriz	59.973	24.657	318.036
Iran	Yazd	35.738	22.655	296.995
Italy	Rome	19.542	14.182	208.573
Italy	Venice	25.093	16.073	209.624
Japan	Hiroshima	22.632	18.369	246.675
Japan	Tokyo	32.265	19.355	249.027
Mexico	Guadalajara	23.451	1.892	415.543
Mexico	Mérida	40.173	1.693	417.866

Nigeria	Kano	57.757	5.976	721.634
Nigeria	Lagos	73.700	0.914	710.523
Pakistan	Karachi	25.394	8.683	611.101
Pakistan	Lahore	22.100	19.135	628.040
Philippines	Davao	60.302	0.640	697.725
Philippines	Manila	62.342	1.297	698.347
Russia	Moscow	104.659	33.153	136.464
Russia	Saint Petersburg	73.412	25.591	142.462
South Africa	Cape Town	66.280	3.550	291.794
Tanzania	Dar Es Salaam	92.050	1.256	495.053
Thailand	Bangkok	64.675	1.878	694.026
Turkey	Istanbul	13.717	13.970	228.080
United Kingdom	London	10.149	8.955	112.128
United Kingdom	Oxford	10.149	8.955	112.128
United States	Chicago	41.963	23.930	282.889
United States	New York	57.884	25.375	275.941

Table 4. SARIMAX RMSE table of top 25 countries and cities with highest population

*3.1.3 **Prophet***

In a groundbreaking move, Facebook, now rebranded as Meta, unveiled the Facebook Prophet library, a cutting-edge tool designed for time series analysis. This library revolutionizes the handling of seasonality and data stationarity parameters, streamlining the process through automated management. The Prophet model, based on an additive methodology, excels in predicting time series data by fitting non-linear trends intertwined with various seasonal patterns occurring annually, monthly, daily, and during special events. It thrives when dealing with strongly seasonal time series and copious amounts of historical data. Our study harnessed Facebook's Prophet model in conjunction with the Analytic Hierarchy Process (AHP), Bottom-Up (BU), and Ordinary Least Squares (OLS) revision approaches to ensure precise forecasts. Facebook, now Meta, introduced the Prophet library for time series analysis, automating seasonality and data stationarity management. Prophet's additive model predicts time series data with nonlinear trends and diverse seasonal patterns. Employing Prophet with AHP, BU, and OLS methods, we found city-level RMSE values superior to country and global levels. The BU method excelled with an RMSE of 1.437. Visualizing in Fig. 5, predicted global temperatures exceeded actuals, affecting RMSE scores. Country-level RMSE values were high across revision methods.

Model	RMSE_City	RMSE_Country	RMSE_total
Prophet AHP	50.370	8906183.279	2223985853.046
Prophet BU	1.437	8899076.068	2223951384.829
Prophet OLS	407.608	335.552	1270.057

Table 5. Prophet RMSE table

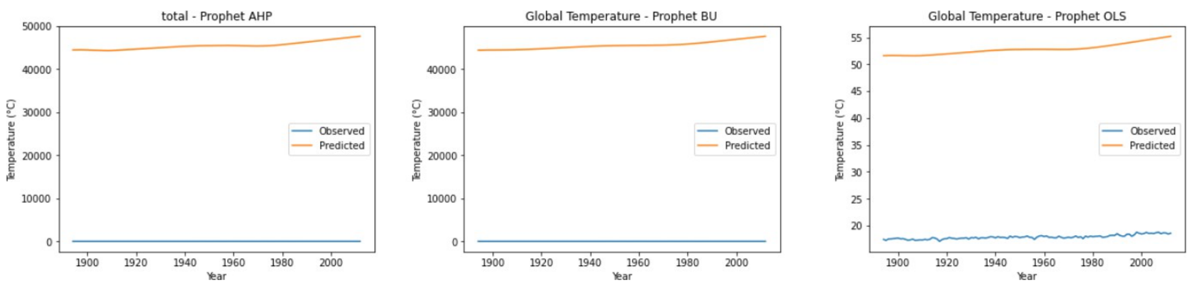


Fig. 5. Observed vs Predicted plot using Prophet - Global temperature

3.1.4 ***Holt -Winters*** **exponential smoothing**

In our research, we leveraged the Holt-Winters exponential smoothing method, pioneered by Charles Holt and Peter Winters, to predict temperatures considering both trend and seasonality. By default, this method assumes no trends or seasonality in the data. Table 6 reveals that city-level RMSE values outshine those at the country and global levels, with the BU method performing the best at 14.91. Fig. 6 visually compares projected global temperatures from the Prophet model using different revision methods against actual values, highlighting significant discrepancies. Table 7 displays city-level RMSE values, significantly lower than country and global levels, with the BU method showing the best fit despite relatively higher RMSE values compared to AHP and OLS methods.

Model	RMSE_City	RMSE_Country	RMSE_total
Holt-Winters AHP	55.795	8908849.551	2224539486.318
Holt-Winters BU	14.908	8913878.911	2224440677.987
Holt-Winters OLS	409.068	341.026	1286.728

Table 6. Holt-Winters RMSE table

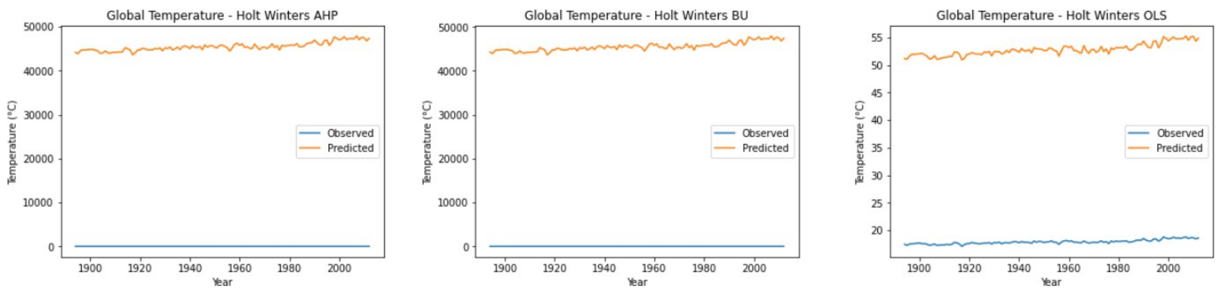


Fig. 6. Observed vs Predicted plot using Holt-Winters - Global temperature

Country	City	RMSE Holt Winters AHP	RMSE Holt Winters BU	RMSE Holt Winters OLS
Bangladesh	Dhaka	30.809	6.565	617.829
Bangladesh	Rajshahi	26.867	7.954	618.721
Brazil	Rio De Janeiro	85.166	1.595	497.598
Brazil	São Paulo	74.963	2.744	496.283
China	Chongqing	17.845	16.750	253.145
China	Shanghai	29.242	22.494	264.291
Congo	Bukavu	40.548	0.202	542.074
Congo	Kinshasa	69.372	0.803	542.273
Egypt	Cairo	7.188	9.562	476.052
Egypt	Luxor	11.907	13.231	475.055
Ethiopia	Addis Abeba	37.308	0.778	394.650
Ethiopia	Gondar	38.135	1.149	394.959
France	Lyon	26.682	15.182	152.777
France	Paris	14.786	12.579	152.376
Germany	Berlin	30.990	17.998	124.557
Germany	Hamburg	25.136	14.616	124.243
India	Delhi	27.210	16.307	684.220
India	Thiruvananthapuram	81.572	0.800	669.933
Indonesia	Jakarta	70.712	0.156	678.257
Indonesia	Makasar	66.590	0.285	678.380

Iran	Tabriz	59.432	25.716	310.660
Iran	Yazd	35.043	23.204	299.314
Italy	Rome	19.130	14.451	207.852
Italy	Venice	24.653	16.438	206.637
Japan	Hiroshima	22.010	18.791	248.466
Japan	Tokyo	31.657	19.783	247.307
Mexico	Guadalajara	24.362	1.690	418.511
Mexico	Mérida	41.770	1.282	421.280
Nigeria	Kano	59.458	5.694	717.548
Nigeria	Lagos	76.070	0.456	711.866
Pakistan	Karachi	26.155	8.496	621.525
Pakistan	Lahore	21.832	19.200	627.690
Philippines	Davao	62.373	0.236	698.339
Philippines	Manila	64.407	0.886	698.317
Russia	Moscow	104.513	35.901	137.833
Russia	Saint Petersburg	73.240	27.716	151.050
South Africa	Cape Town	67.758	3.295	293.927
Tanzania	Dar Es Salaam	94.683	0.751	496.042
Thailand	Bangkok	66.788	1.467	694.812
Turkey	Istanbul	13.337	14.265	232.173
United Kingdom	London	9.927	9.124	111.074
United Kingdom	Oxford	9.927	9.124	111.074
United States	Chicago	41.405	24.912	274.932
United States	New York	57.298	26.317	266.232

Table 7. Holt Winters RMSE table of top 25 countries and cities with highest population

3.2. **Model Comparison**

Evaluating the model's performance solely based on Root Mean Square Error (RMSE) assessments is deemed inadequate for drawing conclusive insights. A comprehensive analysis of the forecasted outcomes is imperative. Our predictions span from monthly temperatures in 2013 to 2050, necessitating a thorough examination of these projections. Visual representations of forecasted temperatures are depicted separately for country, city, and global levels. Additionally, we scrutinized the forecasted global temperature and country-level outcomes by aggregating city-level forecast results.

Our study further delves into aggregating city-level forecast outputs from Arima, SARIMAX, Prophet, and Holt-Winters exponential smoothing models to the global level, contrasting them with actual national temperature data. The consolidated city-level predictions from all three models were extrapolated to the global level to compute global RMSE values, detailed in Table 8. Comparative analysis against RMSE values in Tables 1, 3, 5, and 6 reveals significantly lower RMSE values for the AHP, BU, and OLS methodologies. Line graphs depicting the observed and forecasted global-level data, derived from combined city-level forecasts, are presented in Fig. 7. Notably, the OLS approach in the Auto Arima model projected lower temperature values compared to actual readings, while AHP and BU forecasts exhibited a coherent alignment with measured values. The SARIMAX model's forecasts from the three revision methods indicated consistent trends with almost identical temperature readings. In the Prophet model, forecast outcomes smoothly followed the fluctuations in measured temperature data. The Holt-Winters exponential smoothing model accurately accounted for original temperature variations, mitigating overfitting.

Fig. 8 illustrates the aggregated city-level forecasts from all three models to the global level. Noteworthy trends include the OLS technique's sharp decline in 2013 and subsequent stability in the Auto Arima model. The efficacy of the AHP and BU methods in Auto Arima stems from their ability to track the average temperature trend. In contrast, declining trends projected by the AHP, BU, and OLS methodologies in the SARIMAX model suggest potential forecast inaccuracies. In the Prophet model, unjustifiable fluctuations in AHP and BU forecasts indicate unreliability, while the OLS forecast predicts a steady decline post-2012. Similarly, Holt-Winters' exponential smoothing model forecasts a sharp temperature decline post-2012, remaining stable until 2050. Overall, the AHP and BU methods in Auto Arima offer more reliable global temperature forecasts based on these observations.

Model	**RMSE**
Arima AHP	1.165387
Arima BU	0.252194
Arima OLS	349.264630
Holt Winters AHP	0.200754
Holt Winters BU	0.001348
Holt Winters OLS	345.451053
Prophet AHP	0.215393
Prophet BU	0.019303
Prophet OLS	345.450490
SARIMAX AHP	0.068235
SARIMAX BU	0.078992
SARIMAX OLS	345.342533

Table 8. RMSE - Global temperature, aggregating city level results

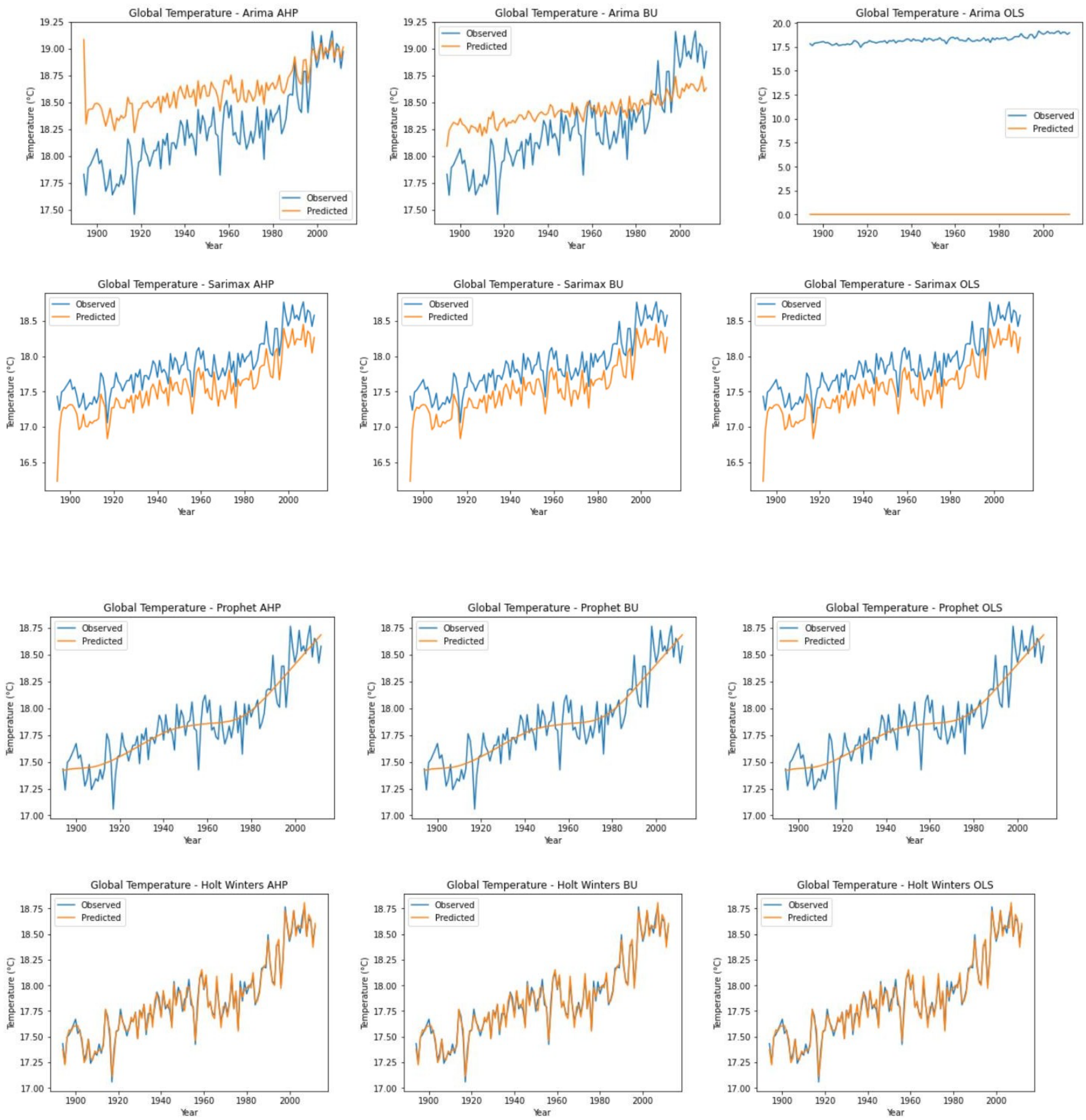


Fig. 7. Observed vs Predicted plot using all model – Global temperature, aggregated from City level results

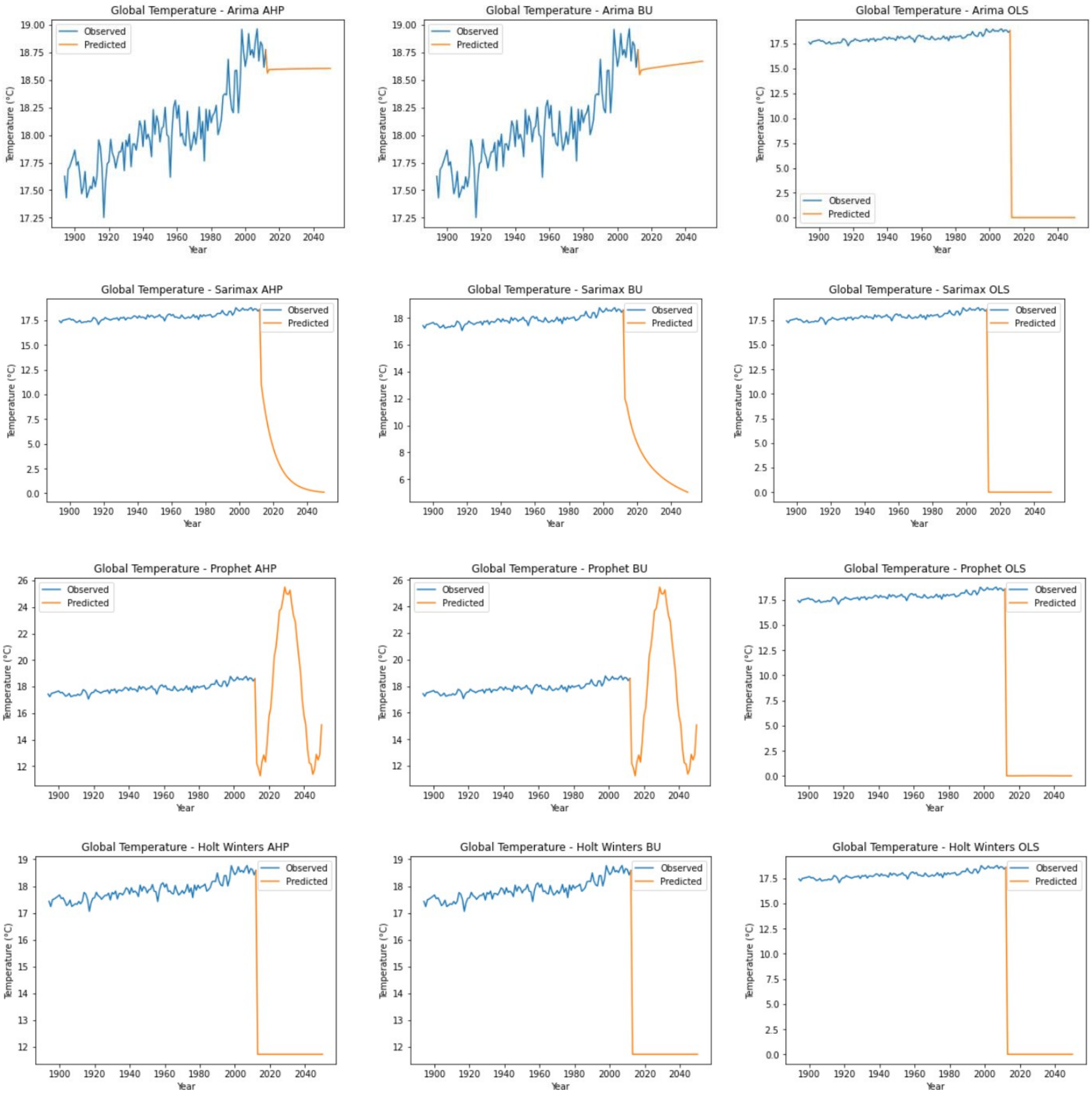


Fig. 8. Global temperature forecast, aggregated from City level results

3.3. Discussion on Forecasted Results

This section presents the outcomes of experiments conducted to predict monthly average temperatures through hierarchical time series forecasting. An evaluation of the results from Arima, SARIMAX, Prophet, and Holt-Winters exponential smoothing models, with OLS, BU, and AHP as revision methods, leads to the following conclusions.

3.1.1 City Level Forecast

The Auto Arima with BU approach demonstrates superior city-level forecasting compared to other models. Fig. 9 illustrates the forecasted values align with the average temperature trend, enhancing its performance. Conversely, some models exhibit erratic trends with high variations, as depicted in Table 9, showcasing the efficacy of the Auto Arima with BU approach through low RMSE values.

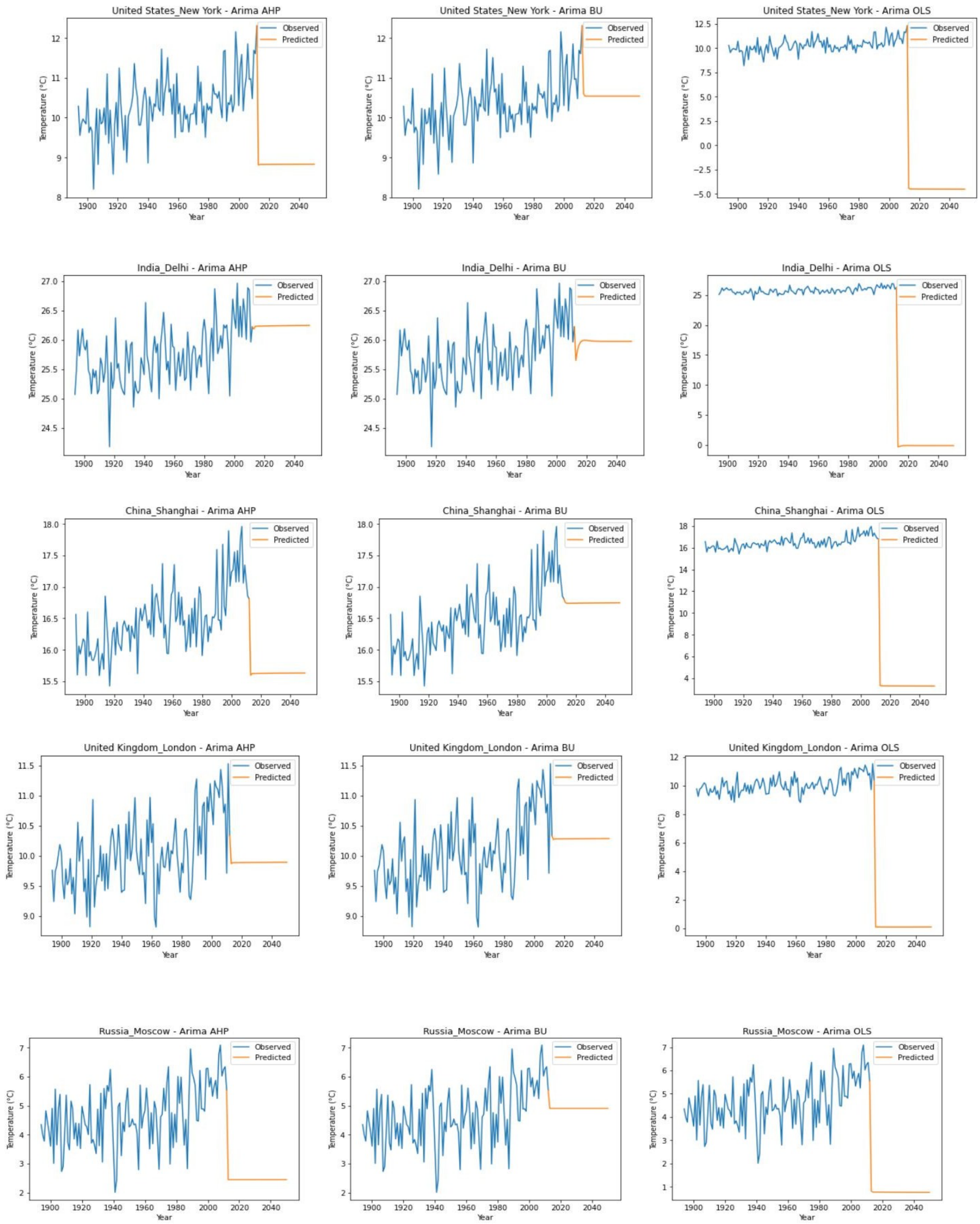


Fig. 9. City level temperature forecast using Arima

In Table 10, temperature predictions for select cities using the Auto Arima BU technique are presented, showcasing successful city-level forecasting. Notably, temperatures are projected to increase by 2.90% in London, 2.21% in Vancouver, and 0.57% in Dongli from 2012 to the predicted values for 2050, indicating a notable rise in land surface temperatures.

Model	RMSE – City Level
Arima AHP	48.111
Arima BU	2.661
Arima OLS	422.523
Holt Winters AHP	55.795
Holt Winters BU	14.908
Holt Winters OLS	409.068
Prophet AHP	50.370
Prophet BU	1.437
Prophet OLS	407.608
SARIMAX AHP	55.252
SARIMAX BU	14.525
SARIMAX OLS	408.973

Table 9. RMSE Table – City level

City	2012	2020	2025	2030	2035	2040	2045	2050
London, United Kingdom	9.99	10.281	10.282	10.283	10.284	10.284	10.285	10.285
Balakovo, Russia	6.40	5.235	5.245	5.254	5.261	5.266	5.270	5.273
Vancouver, United States	10.25	10.474	10.475	10.476	10.477	10.478	10.479	10.480
Phagwara, India	24.3	24.294	24.306	24.303	24.301	24.301	24.300	24.300
Dongli, China	24.5	24.621	24.630	24.636	24.639	24.640	24.641	24.642

Table 10. City level temperature forecast results (in °C) Auto Arima, BU approach

3.1.2 Country Level Forecast

Analysis results reveals that all models, including Auto Arima, SARIMAX, Prophet, and Holt-Winters exponential smoothing, produce unrealistic temperature values at the country level. By aggregating city-level forecasts, we obtained more accurate national-level predictions, with the Auto Arima BU approach yielding the best results. Fig. 10 highlights the model's ability to maintain average temperatures, contrasting with other models displaying inexplicable trends and high variances. Table 11 showcases low RMSE values for the country-level model, emphasizing the suitability of the Auto Arima with BU method.

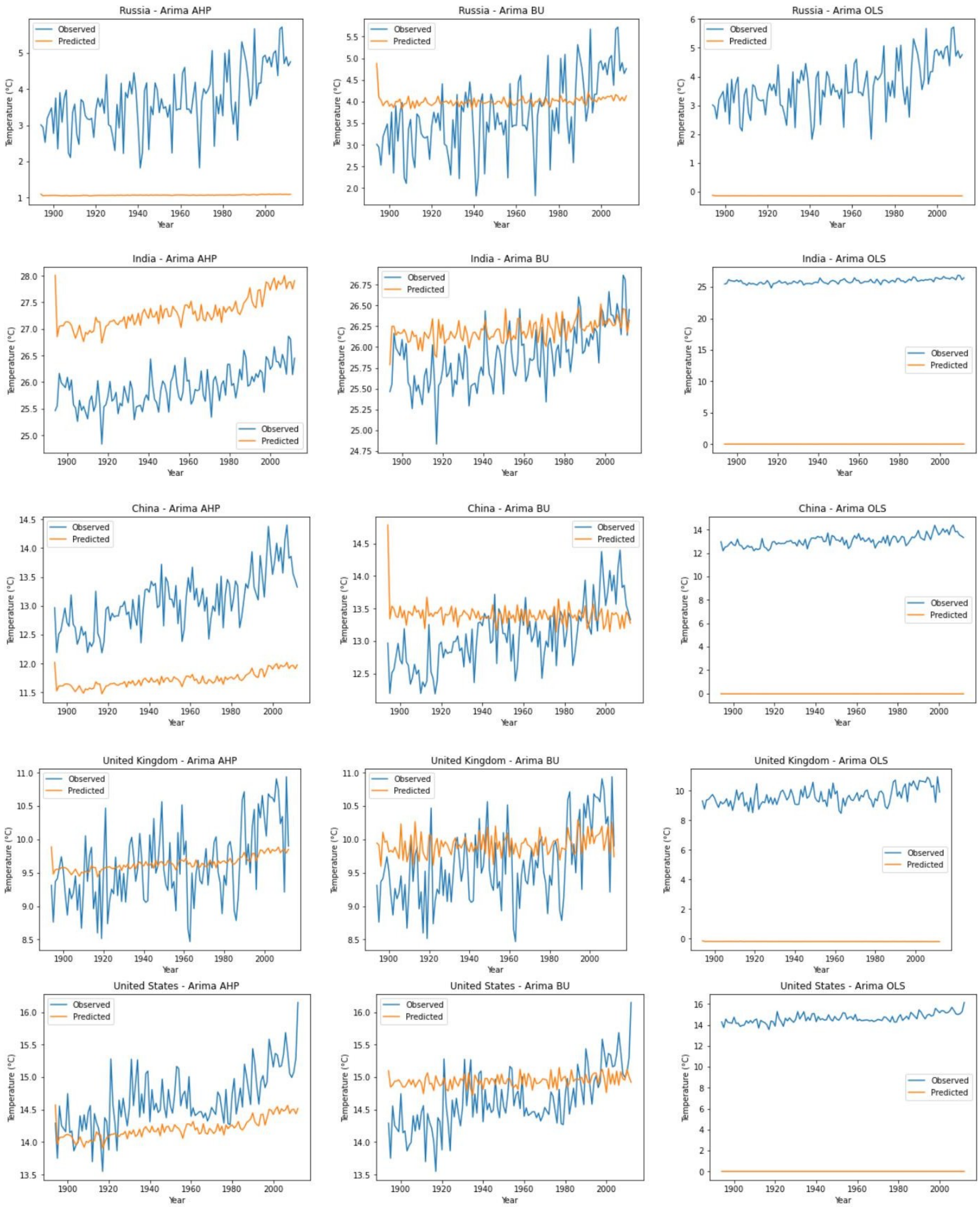


Fig. 10. Observed vs Predicted plot using Arima – Country level temperature, aggregated from City level results

Model	RMSE – Country Level
Arima AHP	3.121

Arima BU	0.186
Arima OLS	407.270
Holt Winters AHP	3.241
Holt Winters BU	0.016
Holt Winters OLS	387.928
Prophet AHP	3.248
Prophet BU	0.127
Prophet OLS	387.932
SARIMAX AHP	2.856
SARIMAX BU	0.141
SARIMAX OLS	387.767

Table 11. RMSE Table – Country level, aggregating city level results

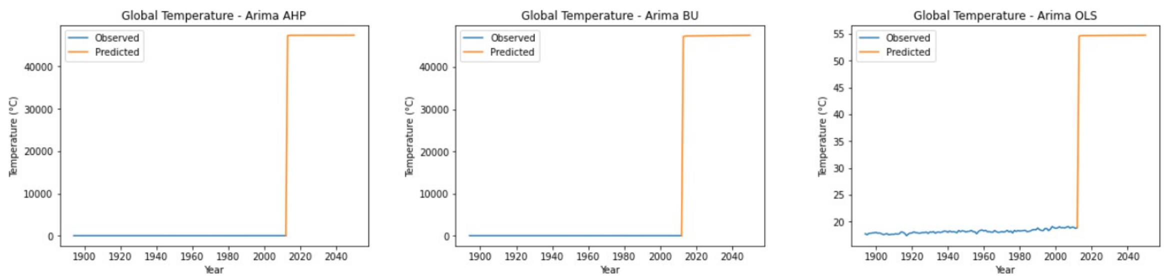
Country	2012	2020	2025	2030	2035	2040	2045	2050
United Kingdom	15.88	9.986	9.985	9.982	9.977	9.972	9.966	9.960
Russia	4.5	4.031	4.032	4.032	4.032	4.032	4.031	4.031
United States	15.8	15.028	15.033	15.037	15.039	15.041	15.043	15.045
India	26.19	26.048	26.050	26.053	26.057	26.060	26.064	26.068
China	13.06	13.380	13.382	13.384	13.385	13.386	13.387	13.387

Table 12. Country level forecast results (in °C) Auto Arima-BU approach, aggregating city level results

Table 12 displays predicted temperature values for selected nations, derived from city-level results using the Auto Arima BU approach, affirming successful country-level forecasting. Notably, China's temperature is projected to increase by 2.47% from 2012 to the forecasted values for 2050, warranting attention.

3.1.3 Global Temperature Forecast

Fig. 11 indicates that models, including Auto Arima, SARIMAX, Prophet, and Holt-Winters exponential smoothing, generate extreme temperature forecasts at the global level. However, successful predictions are achieved by combining city-level results, with the Auto Arima BU and AHP techniques outperforming other models.



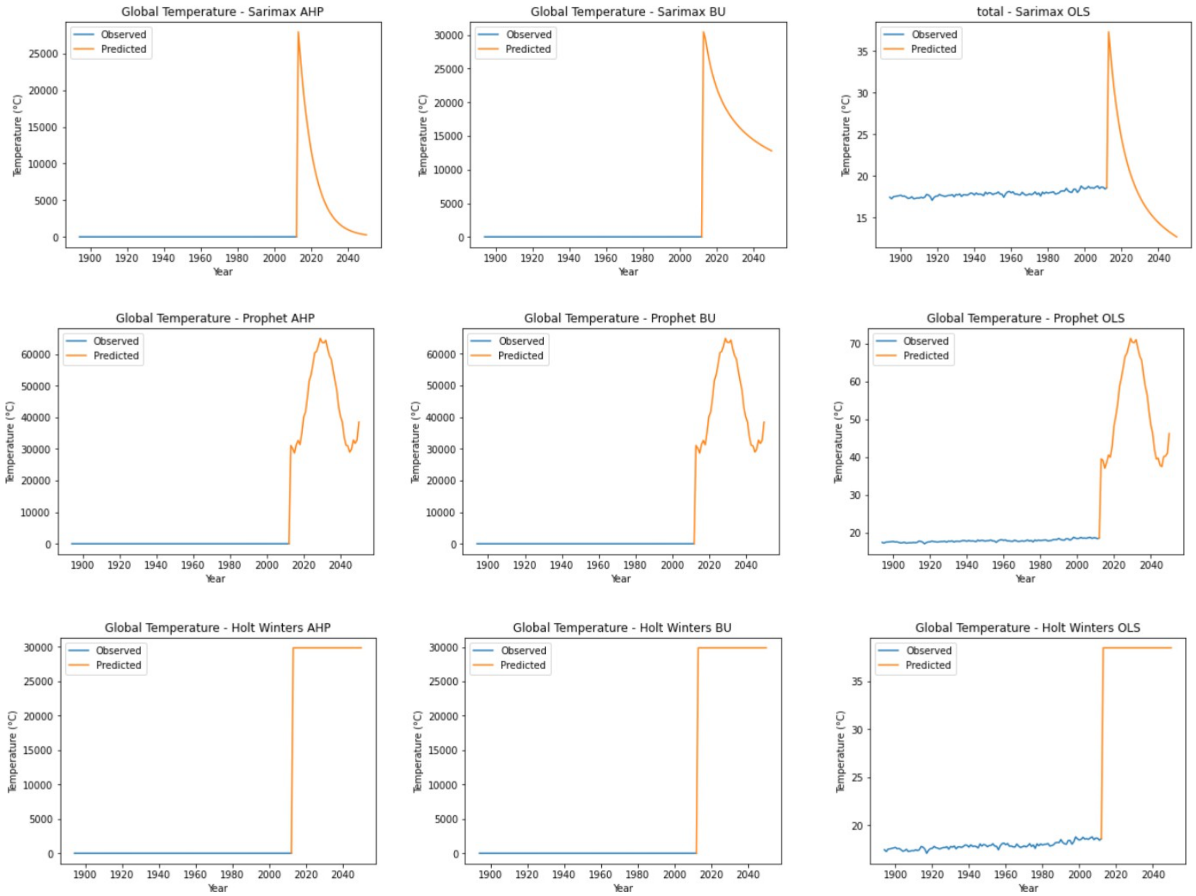


Fig. 11. Global temperature forecast using Arima, SARIMAX, Prophet and Holt Winters

Fig. 8 demonstrates how the Auto Arima BU and AHP methods maintain average temperatures effectively, contrasting with models showing erratic trends. Table 13 displays low RMSE values for the global model, indicating the efficacy of the Auto Arima with BU method.

Model	RMSE – Country Level
Arima AHP	0.408
Arima BU	0.050
Arima OLS	366.394
Holt Winters AHP	0.201
Holt Winters BU	0.001
Holt Winters OLS	345.451
Prophet AHP	0.215
Prophet BU	0.019
Prophet OLS	345.450
SARIMAX AHP	0.068

SARIMAX BU	0.079
SARIMAX OLS	345.343

Table 13. RMSE Table – Global level, aggregating city level results

	2012	2020	2025	2030	2035	2040	2045	2050
Temperature	18.57	18.597	18.598	18.600	18.601	18.602	18.603	18.604

Table 14. Global level forecast results (in °C) Auto Arima, AHP approach

	2012	2020	2025	2030	2035	2040	2045	2050
Temperature	18.57	18.606	18.618	18.628	18.639	18.648	18.658	18.668

Table 15. Global level forecast results (in °C) Auto Arima, BU approach

Tables 14 and 15 present predicted global temperature values obtained by aggregating city-level results using the Auto Arima AHP and BU approaches, respectively. These findings underscore the accuracy of the Auto Arima BU method in forecasting global temperatures, with a projected 0.52% increase from 2012 to 2050.

4. Conclusions

In this research, an extensive analysis was conducted on monthly average temperature data spanning from 1894 to 2012 across 159 nations, forecasting temperatures up to 2050 for prominent cities. Various models including Auto Arima, SARIMAX, Prophet, and Holt Winters exponential smoothing with BU, AHP, and OLS revision techniques were evaluated, with a robust model identified that surpassed competitors in forecast accuracy. The study emphasized the critical role of land surface temperature in the Earth's climate system, highlighting its influence on vital processes like water and energy transfer and vegetation growth. By employing hierarchical time series analysis, the research aimed to understand and forecast land surface temperatures in major cities globally, revealing a notable temperature rise trend. The findings underscored the significance of hierarchical forecasting to achieve reliable predictions across different levels of hierarchy, with the Auto Arima model utilizing the BU method demonstrating superior performance at the city level. The study highlighted a 0.52% global temperature increase by 2050, emphasizing the urgent need for proactive measures in light of escalating temperatures.

This research contributes substantially to the understanding of Earth's warming trends and the impacts of human-induced greenhouse gas emissions on climate and ecosystems. By exploring hierarchical time series forecasting models such as Auto Arima, SARIMAX, Prophet, and Holt Winters exponential smoothing, and adopting the Auto Arima model with BU revision as the preferred approach, the study provides valuable insights into forecasting methodologies.
Future work therefore can include refining models through techniques like PHA, FP, WLSS, and WLSV revisions, as well as adjusting Auto Arima and SARIMAX parameters for enhanced precision. The study's comprehensive approach and utilization of hierarchical time series forecasting techniques signify its relevance in addressing complex business challenges requiring accurate time series forecasting at various hierarchical levels, thus offering valuable contributions to the field.

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