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Research Article

Wildfire Prediction in the United States Using Time Series Forecasting Models

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Abstract: Wildfires are a widespread phenomenon that affects every corner of the world with the warming climate. Wildfires burn tens of thousands of square kilometres of forests and vegetation every year in the United States alone with the past decade witnessing a dramatic increase in the number of wildfire incidents. This research aims to understand the regions of forests and vegetation across the US that are susceptible to wildfires using spatiotemporal kernel heat maps and, forecast these wildfires across the United States at country-wide and state levels on a weekly and monthly basis in an attempt to reduce the reaction time of the suppression operations and effectively design resource maps to mitigate wildfires. We employed the state-of-the-art Neural Basis Expansion Analysis for Time Series (N-BEATS) model to predict the total area burned by wildfires by several weeks and months into the future. The model was evaluated based on forecasting metrics including mean-squared error (MSE)., and mean average error (MAE). The N-BEATS model demonstrates improved performance compared to other state-of-the-art (SOTA) models, obtaining MSE values of 116.3, 38.2, and 19.0 for yearly, monthly, and weekly forecasting, respectively.

Keywords: ***Deep learning; Forecasting; Time-series; Wildfires***

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1. Introduction

Every year wildfires burn through millions of acres of forests and natural reserves in the United States alone, destroying various wildlife and ecological habitats[1]. Furthermore, wildfire suppression operations can accrue huge expenses on the government's monetary and fiscal plans. Generally, states are legally responsible for their suppression operations with optimal planning for resource allocation. Wildfire forecasting is beneficial for the effective distribution of wildfire suppression efforts and their resources. Weekly wildfire forecasts at state level can help minimise suppression costs and ensure optimal resource allocation. Even in worst-case scenarios, with the annual expenditure for suppression operations averaging over a billion dollars per year over the past two decades[2], marginal improvements in the suppression efficiency can lead to a substantial reduction in the costs for the operations. While occurrences of wildfire incidents and their sizes are largely dependent on a number of factors[3], these events are chaotic and stochastic in nature. Hence, forecasting wildfires is a challenging task overall. Time series models are used for forecasting time-varying data by learning the patterns and trends observed from anterior observation points and extrapolating future values based on these learned patterns. Many statistical, machine learning

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[1] https://apps.dtic.mil/sti/citations/AD1143321

[2] https://www.nifc.gov/fire-information/statistics/suppression-costs

[3] https://www.nps.gov/articles/wildfire-causes-and-evaluation. html

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and deep learning approaches have previously been explored for forecasting time series data [1,2]. Some recent univariate approaches include the use of models such as autoregressive (AR) [3], moving average (MA), autoregressive moving average (ARMA) [4], autoregressive integrated moving average (ARIMA), and autoregressive recurrent network (DeepAR). Additionally, a variety of univariate and multivariate machine learning state-of-the-art approaches including long short-term memory (LSTM) [5], LSTM and Box-Cox [6], N-BEATS [7], Spacetimeformer [8], Temporal Fusion [9], and Transformer (TFT) [10] have also been employed in the past for time series analysis. In this study, we investigate the potential of the advanced deep learning-based, state-of-the-art forecasting model N-BEATS, to predict the total area burned (TAB) from wildfire events at state level across the United States. The study analyzes the N-BEATS model against MLP and LSTM baseline models for wildfire forecasting accuracy, utilizing a dataset from ArcGIS Hub. The dataset includes wildfire information and was pre-processed with QGIS, Geopandas, and Pandas for state-level analysis. Both baseline models, trained over, are rated on MSE values to gauge prediction accuracy. MSE is a widely used metric for evaluating the accuracy of predictive models. It quantifies the average squared difference between predicted values and actual values in a dataset. Furthermore, we discern meaningful spatiotemporal patterns from wildfire events across the United States using kernel density maps. Figure 1 shows the summary of the contribution.

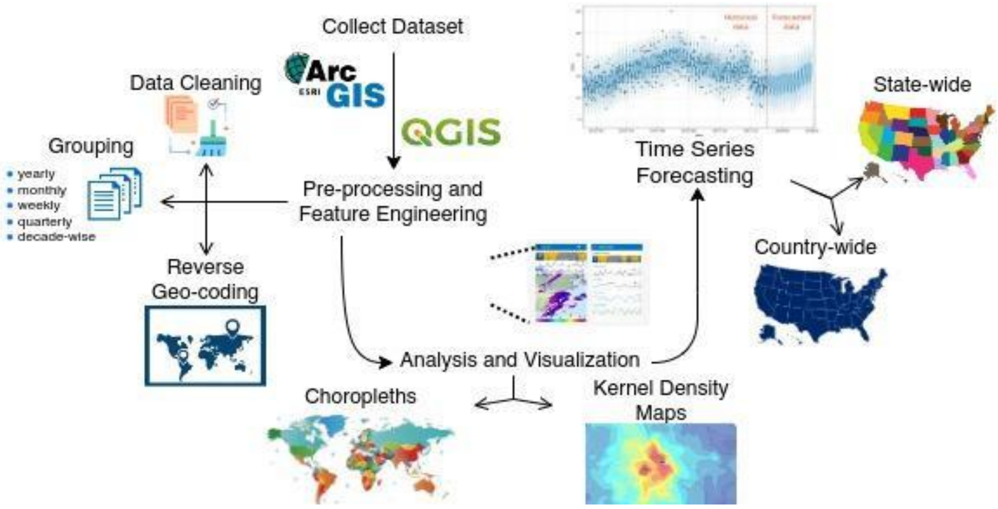


Figure 1. A block diagram detailing the contributions

2. Related Works

This section reviews the prior art and literature relevant to our research. Numerous techniques have previously been examined in the literature for wildfire forecasting.

Preisler and Westerling [11] developed a statistical wildfire forecasting model using logistic regression and spline functions that is capable of extrapolating large wildfire events one month ahead. Introducing piecewise polynomials enhanced the logistic regression model's ability to learn non-linear features and, hence, making it more reliable as a forecasting model. A number of climatic and topographic variables were combined and projected on a plane of 1 by 1-degree grid size. The data were grouped by month. A probability distribution characterised by the spread and ignition of wildfires was approximated from the resulting time-varying data. The distribution was analyzed using logistic regression in conjunction with piecewise polynomial functions.

Rubí *el al.* [12] offered a comprehensive literature analysis on wildfire risk prediction, reviewing several studies that employed machine learning algorithms to forecast wildfire occurrences. It analyzed the techniques, features, and outcomes of numerous significant researches, comparing their approaches, model performances, and the significance of different features in wildfire prediction. The study then focused research undertaken globally, with an emphasis on applying these models to the Brazilian Federal District region, underlining the relevance of selecting relevant models and features for specific geographic areas.

Nur *et al.* [13] proposed an integrated approach to predicting wildfire vulnerability in Sydney, Australia, utilizing Support Vector Regression (SVR) supplemented by metaheuristic optimization methods Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO). It utilizes geographic information system (GIS) tools and remote sensing data to investigate factors impacting wildfire occurrences. The research examines the performance of hybrid machine learning models against traditional SVR, demonstrating that the optimized models greatly enhance prediction accuracy.

Hoang *et al.* [14] proposed a novel stochastic temporal video-predicting model for wildfire detection from a series of geospatial wildfire images. The model was based on stochastic residual neural networks and state space models. The model was evaluated on the GOES-16 dataset for benchmarking. However, their data collection length was around 56 days with a limited time frame. Therefore, our study goes beyond the typical video prediction abilities of the stochastic dynamic model by offering a direct benefit in forecasting and handling natural disasters.

Hernandez *et al.* [15] used three meteorological covariates and two remotely sensed fire variables to model a conditional density function for identifying wildfire risks. The authors collected these wildfire data from the MODIS catalogue. Nevertheless, their method relies mostly on statistics, using past data and weather variables to predict fire hazards. Our study signifies a transition from a statistical approach to a machine learning-based method, which is expected to enhance prediction accuracy and effectively manage intricate nonlinear patterns in data. The improved efficiency of our method compared to prior work may be attributed to its direct applicability to a wider geographical area and its enhanced ability to capture complicated spatiotemporal interactions more efficiently. Beckage and Platt [16] used an autoregressive moving average (ARMA) model to forecast wildfires at Everglades National Park in southern Florida, three months and twelve months beforehand. The authors employed the amount of area burned as the primary covariate for the forecasting model. The dataset was obtained from ENP fire records. Besides, this approach depends mainly on statistical modeling of past data to create predictions regarding wildfire seasons. Whereas, our research employs sophisticated deep learning techniques (N-BEATS) and geospatial analysis (kernel density maps) to forecast and examine wildfire occurrences throughout the United States. This methodological improvement integrates machine learning for predictive accuracy and geospatial approaches for spatial pattern detection, providing possibly more precise and complete insights into wildfire dynamics on a bigger scale. This method has the potential to result in more efficient and focused wildfire management tactics.

Gudmundsson *et al.* [17] analyzed the predictability of wildfires from large-scale droughts in southern Europe using logistic regression. The authors utilized a standardized precipitation index (SPI) as their dataset which was derived from E-OBS. The model predicted monthly probabilities, up to two months in advance, of the above-normal total area burned based on the prior meteorological drought that was proxied by the SPI. For evaluating the models, Receiver Operating Characteristics (ROC) statistics were computed from leave-one-out cross-validation training of the logistic regression model. However, the study employed logistic regression to forecast wildfire activity based on meteorological dry conditions. It illustrates that lengthy lead-time projections of wildfire risk are viable in southern Europe using historical data on dry conditions. But in terms of managing vast quantities of data, the model might not do well in terms of accuracy. This will hinder the practicality and scalability of model improvement. But our study confirms that employing a more advanced N-BEATS model that consists of a collection of stacks of multi-layer fully connected (FC) layers. Each stack comprises a succession of blocks, each built up of multi-layer FC layers injected with ReLU nonlinearities.

Kaur and Sood [18] proposed a multifaceted, fog-aided, Internet of Things (IoT) based architectural paradigm for wildfire prediction and forecasting. Two models, Naïve Bayes (NB) and autoregressive integrated moving average (ARIMA), were tasked with predicting and forecasting the wildfire vulnerability level of terrains in the cloud, respectively. An additional model, support vector machines (SVM), was used to predict the burnt forest area. Several sensing devices were employed to sample wildfire influent parameters. The fog layer was concerned with energy conservation, i.e. energy efficient sampling, and dimensionality reduction using one-way ANOVA method and principal component analysis (PCA), respectively. The final layer was entrusted with the responsibility of storing, processing, and analysing the pre-processed data. Our contribution advances over their work by applying the N-BEATS deep learning model and thorough spatial analyses through choropleth and kernel density maps, enabling more accurate wildfire predictions and insights into spatiotemporal patterns across the United States. Enhanced data pre-processing and the use of PyTorch for setting up models further contribute to the efficiency and sophistication of our approach, potentially offering richer, more actionable forecasting predictions.

Song and Wang [19] explored three statistical models for monthly wildfire forecasting including a generalised linear model, regression tree and neural networks, with the latter trained using Levenberg–Marquardt backpropagation. The monthly wildfire dataset was collected from Global Fire Emissions Database (GFED). The forecasting models performed better during high-fire seasons as compared to the low-fire seasons. Additionally, significant differences in performance were observed in tropics and subtropics regions as compared to temperate and boreal regions. However, their study produced monthly wildfire predictions from their used models on the contrary our data collection process focuses on the weekly, monthly and yearly forecasts.

Cheng *et al.* [20] proposed an ensemble approach to wildfire spread forecasting that utilised a forward and inverse modelling scheme and a reduced-order modelling (ROM) scheme. The model was evaluated on the 2018 California Chimney and Ferguson wildfire dataset. The ROM scheme comprised several dimensionality reduction and compression techniques including Principal Component Analysis (PCA), Convolutional Autoencoding and Singular Value Decomposition Autoencoding. The resultant ensemble of perturbed parameters was sampled using Latin Hypercube Samplings (LHSs) to predict latent variables using Random Forest Regression and K-Nearest Neighbor Regression. Lastly, a multi-layer perceptron was employed to predict the fire propagation from the latent space variables. The model was optimised and tuned using a novel latent data assimilation (LDA) method. Moreover, our study potentially prevails over their ensemble technique by focusing on direct, state-level wildfire prediction utilizing the N-BEATS model and geographical analysis through choropleth and kernel density maps. It offers a simplified, efficient forecasting strategy, boosted by extensive data preparation and the application of latest deep learning tools like PyTorch, providing a thorough understanding of wildfire dynamics.

Preisler *et al.* [21] developed a statistical model to forecast large fire occurrences in the US using fire danger indices and other variables. The study analysed six years of fire data from the Western US and found that the Significant Fire Potential Outlook and Energy Release Component significantly influenced the probability and number of significant fires. The model provided a quantitative risk index and forecast maps, aiding fire managers in resource allocation and decision-making. The study emphasised the importance of accurate fire forecasts for effective fire management. Their study focuses on statistical modeling employing fire danger indexes for wildfire forecasting in the Western US, giving tools for fire management. Our technique, by comparison, utilises the N-BEATS deep learning model with spatial analysis for a broader, countrywide prediction. The significant distinction resides in technique where they focus on statistical rather than a new advanced deep learning model and scope, with our study utilizing sophisticated spatial analysis for increased knowledge of wildfire patterns, enabling possibly more detailed and dynamic forecasting capabilities.

3. Research Methodology

3.1. Data Sources and Pre-processing

The dataset, acquired from ArcGIS Hub, comprises the date of first occurrence or ignition, geographic coordinates, acres burned from the fire event, fire type, etc. The dataset was filtered to discard all non-wildfire-related fire events. Software and application packages such as QGIS, Geopandas, and Pandas were used for pre-processing the data for training. QGIS: An open-source Geographic Information System (GIS) application that enables users to create, modify, view, analyze, and publish geospatial information. In this setting, QGIS was utilized to connect state polygons with geographic vector points for state-level wildfire forecasting. Geopandas which is a Python module that extends the datatypes used by pandas to allow spatial operations on geometric types. It was applied for geospatial data processing and analysis, simplifying procedures like spatial joins and overlays. Pandas: which is a Python library providing high-performance, easy-to-use data structures, and data analysis capabilities. It was applied for data pre-processing activities such as filtering, cleaning, and preparing the wildfire dataset for training. Geopandas, Geopy and Pandas modules were used inside a Jupyter Notebook environment for further pre-processing and preparation of the data for training. Rows with missing values were dropped. For state-level forecasting, states with less than 3 million acres of total area burned from wildfires in the past 38 years were discarded for their lack of temporal variations. For model deployment and experimentation, we used a popular deep-learning framework called PyTorch.

3.2. Choropleth and Kernel Density Maps

Choropleth maps provide a convenient way to visualise and analyse time-varying data via thematic maps[4]. We used choropleth maps to understand wildfire patterns over the past three decades. The state boundaries were collected from ArcGIS Hub and the coordinate points were reverse geocoded to obtain the names of their corresponding states. Kernel density maps are another way of analysing geospatial data. Kernel density maps estimate the concentration of features in the area surrounding those features. These maps can be created for both point and line features. It does so by fitting a smooth curved surface over each neighbouring point. The intensity of the kernel density map is greatest at the location of the point feature and decreases as the distance from the point increases, eventually becoming zero at the search radius distance from the point. The kernel density map only considers a circular area around the point. The total value of the kernel density map for a point is determined by the value of the population field for that point, or is set to 1 if no population value is specified. To determine the density of the kernel heat map at each cell in the output raster, the values of all the kernel density maps for the point features are added together at the location of each raster cell[5].

3.3. N-BEATS Forecasting Model

The Neural Basis Expansion Analysis for Time Series (N-BEATS) model, as proffered by Oreshkin *et al.* [5], is composed of a collection of stacks of multi-layer fully connected (FC) layers. Each stack comprises a sequence of blocks, each made up of multi-layer FC layers infused with ReLU nonlinearities. The l^{th} block takes in an input x_l that results from the output of the FC layer, and predicts the forward and backward basis expansion coefficients θ^f and θ^b busing a set of linear projection layers as described by the following equations:

$$\theta_l^f = LINEAR_l^f\ (h_l) \quad (1)$$

$$\theta_l^b = LINEAR_l^b\ (h_l) \quad (2)$$

where hl is the output of the aforementioned FC layer. Two shared basis networks g^b and g^f employ these basis coefficients to compute the forward forecast $\hat{y}_l$ of length H, where H is the forecast horizon; and the best estimate (backcast), $\hat{x}_l$ of lookback window ηH, based on the trainable weights of the l^{th} block. The architecture design was motivated by the need for optimization of the accuracy of $\hat{y}_l$ from the appropriate mix of basis vectors from g^f. $\hat{x}_l$, on the other hand, is optimised to refine the input components. Hence, the equations for computing $\hat{x}_l$ and $\hat{y}_l$ are as follows:

$$\hat{y}_l = \sum_{i=1}^{dim(\theta_l^f)} \theta_{l,i}^f v_i^f \quad (3)$$

$$\hat{x}_l = \sum_{i=1}^{dim(\theta_l^b)} \theta_{l,i}^b v_i^b \quad (4)$$

where v_i^f and v_i^b are forecast and backcast basis vectors. As a result, the final outputs of block l are defined as follows:

$$\hat{y}_l = V_l^f \theta_l^f + b_l^f \quad (5)$$

$$\hat{x}_l = V_l^b \theta_l^b + b_l^b \quad (6)$$

where v_i^f and v_i^b are both basis matrices and, b_l^f and b_l^b are the corresponding bias terms. The computation of the forecast and the backcast vectors are accompanied by two residual branches each for every l^{th} block in a stack. The forecasts are then aggregated in a hierarchical manner to produce the model output $\hat{y}$ whose length is parameterized by forecast horizon H. This is mathematically represented as follows:

$$x_l = x_{l-1} - \hat{x}_{l-1} \quad (7)$$

$$\hat{y} = \Sigma_l \hat{y}_l \quad (8)$$

[4] https://geographicdata.science/book/notebooks/05_choropleth.html

[5] https://bookdown.org/epeterson_2010/docs/introduction-to-kernel-density-estimation.html

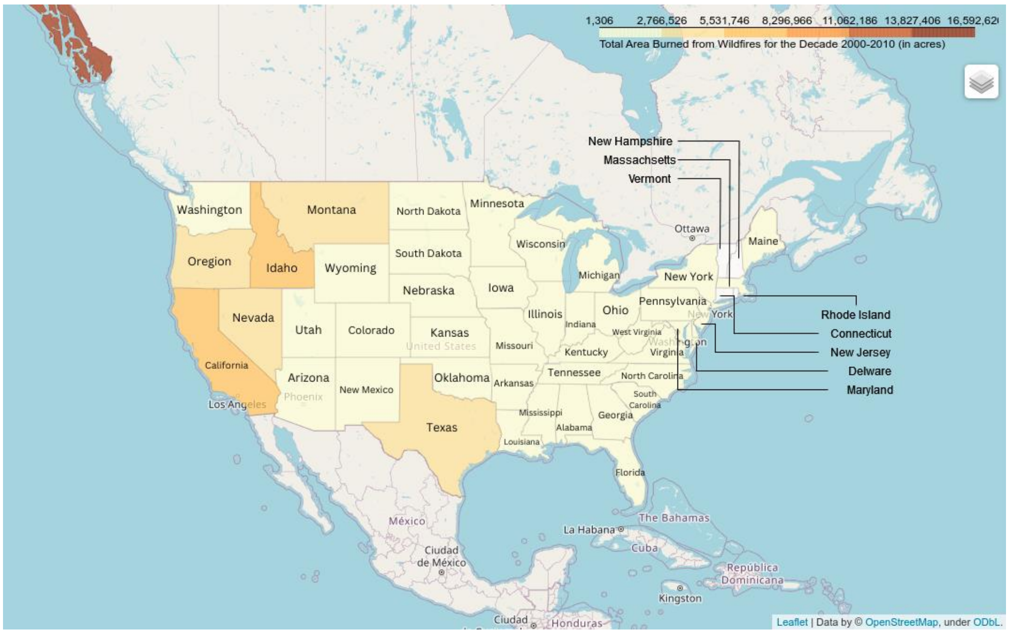
In the last equation, the forecast vector $\hat{y}$ is computed as the sum of all partial forecasts $\hat{y}_l$. By analysing wildfire data, the model can identify and predict regular, cyclical, recurring, and fluctuating patterns, hence, allowing it to function as a seasonal and trend forecasting model.

4. Results and Discussions

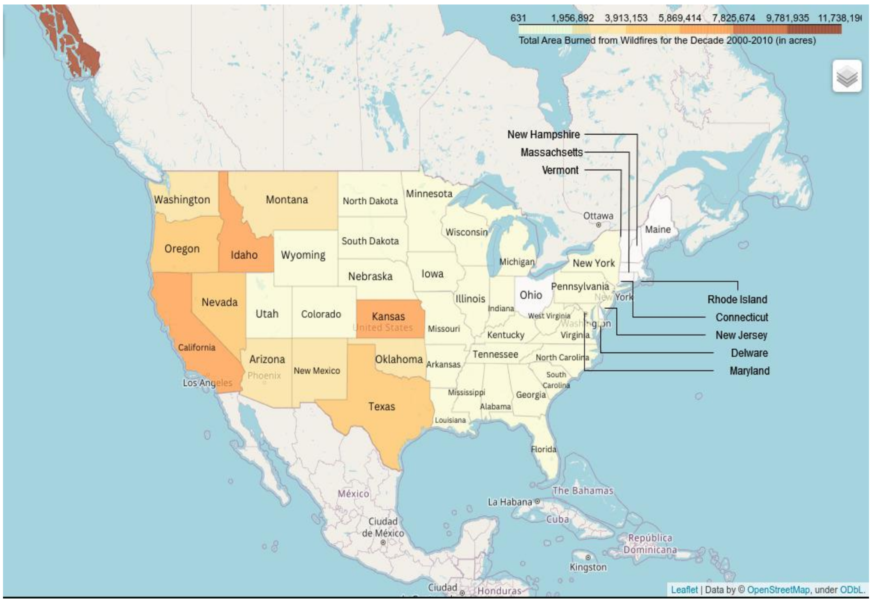
4.1. Data Analysis

By using state-level choropleth maps and kernel density maps, we were able to uncover meaningful patterns in the data. The figures below show the results of our analysis (the state of Alaska has been partially occluded in the following figures for brevity):

(a)



(b)



(c)

Figure 2. Total area burned across last three decades (1990-2020): (a) Total area burned (in acres) for the decade 1990-2000, (b) Total area burned (in acres) for the decade 2000-2010 and (c) Total area burned (in acres) for the decade 2010-2020

Throughout all three decades, the state of Alaska, having the highest forest biomass among all the states, indicated the highest amount of area burned. Figure 2(a) demonstrates the highest TAB in the states of California, Nevada and Idaho from the year 1990 to 2000. In Figure 2(c), the TAB has more than doubled across all the states in the following decade with the state of California, Nevada, Idaho, Oregon, Montana and Texas being amongst the top ten states. Lastly, Figure 2(c) illustrates a steady increase in the total area burned across all the states with high forest biomass. The state of Kansas in particular observed a dramatic increase in TAB in contrast to the past two decades. Further analysis of the wildfire data using kernel density maps demonstrated distinct patterns.

The data were grouped together based on the first two and last two quarters for each year. Performing temporal kernel density map analysis revealed the following: The first half of a particular year (January to June) witnessed the highest occurrences of wildfires in the southern states. In contrast, the western states tend to experience a higher frequency of wildfires during the latter half of the year. This is illustrated in Figure 3. Despite a marginal decrease in the total area affected by fires in the past decade, effectively combating and suppressing wildfires remains a pressing issue.

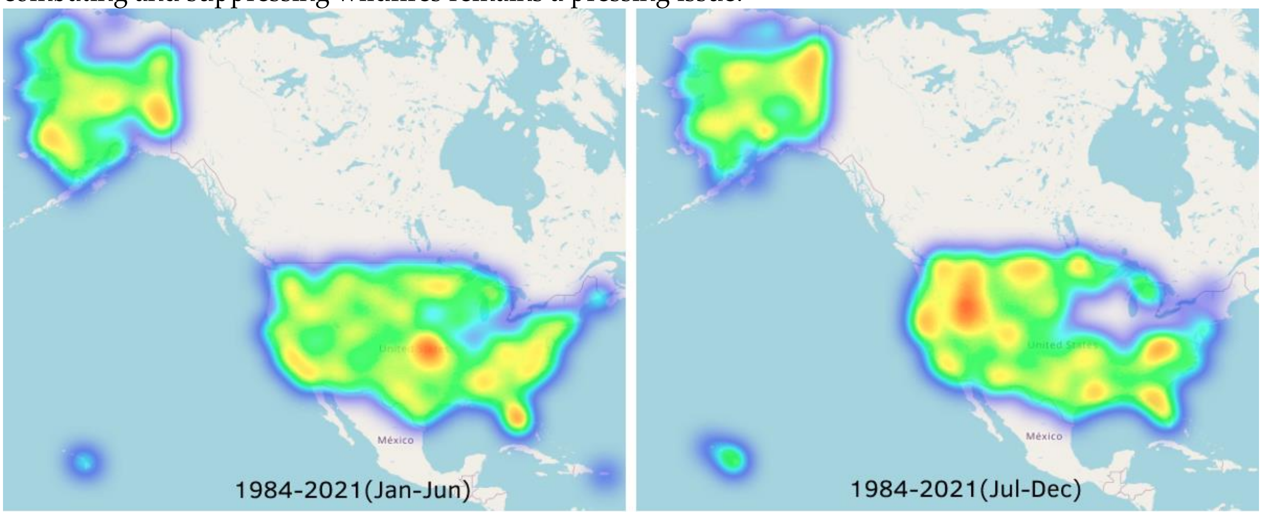


Figure 3. (Left): Kernel density map of wildfire events from January to June for the years 1984-2021; (Right): Kernel density map of wildfire events from July to December for the years 1984-2021

4.2. N-BEATS Forecasting

The model was configured to have three layers of trend blocks with 256 dimensions, followed by three layers of seasonality blocks of 256 dimensions each. The models were trained for over 1000 epochs with a learning rate of 1×10−4 and a forecast horizon of 5. The lookback parameter was set to 7. The model suffered from severe overfitting in some instances of state-wide forecasts including Washington, Oklahoma, and California. On the other hand, in the case of the weekly, monthly, and yearly countrywide forecasts, the model prediction exhibits improved accuracy and loss scores with an MSE of 19.018 and 38.229, respectively. Table 1 shows the performance of the N-BEATS model in forecasting the Total Area Burned (TAB) from wildfires across different intervals at a nationwide and state-wide level. It displays the Mean Squared Error (MSE) for annual, monthly, and weekly forecasts. The MSE values represent the model's accuracy, with lower numbers reflecting more accurate predictions. For countrywide projections, the MSE is highest for yearly intervals (116.346) and lower for monthly (38.229) and weekly (19.018) intervals, suggesting the model performs better at shorter forecasting intervals.

Figure 4 illustrates the countrywide forecasting results, the disparity in yearly estimates, where the model overestimated the area burned, demonstrates the problems in capturing long-term patterns and external variables that may influence wildfire severity. The improved performance in monthly projections reflects the model's strength in recognizing seasonal patterns and short-term climate influences on wildfire incidence. The difficulty with weekly projections in projecting trends appropriately could be related to the model's susceptibility to short-term swings or lack of data on immediate causes driving wildfire spread. This underscores the necessity of integrating more granular data and modifying model parameters for improved short-term forecasts.

Table 1. Results of the N-BEATS model at (a) countrywide forecasting of TAB from wildfires

Interval	Mean Squared Error (MSE)
yearly	116.346
monthly	38.229
weekly	19.018

Table 2. Results of the N-BEATS model at state-wide forecasting of State-level TAB from wildfires

State	Mean Squared Error (MSE)	State	Mean Squared Error (MSE)
Alaska	16.124	Oregon	16.015
Arizona	6.981	Utah	10.283
California	150.091	Kansas	15.092
Colorado	22.275	Montana	45.696
Florida	16.940	Oklahoma	381.019
Idaho	8.434	Texas	1.138
Nevada	13.707	Washington	327.111
New Mexico	6.087	Wyoming	0.987

For state-wide predictions, the model had difficulty accurately predicting state-level trends for TAB due to the lack of significant fluctuating, cyclic, and recurring patterns in its data. Wyoming and Texas had the lowest MSE of 0.987 and 1.138, respectively, amongst all the states.

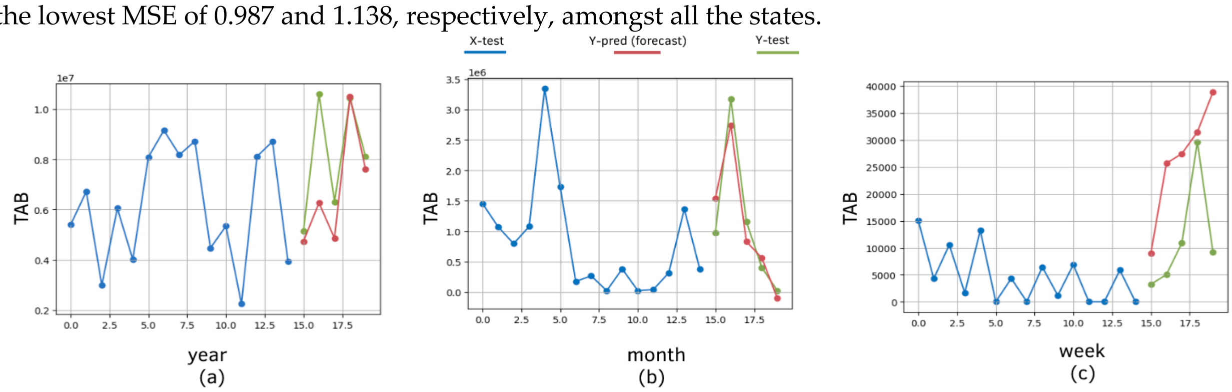


Figure 4. (a) Yearly, (b) Monthly (c) Weekly forecasts of TAB from wildfires

For evaluating the performance of the N-BEATS model, we compare its results with two baseline models: MLP (Multi-Layer Perceptron) and LSTM (Long Short-Term Memory). The MLP model is a feedforward neural network known for learning complex patterns, while the LSTM model is a recurrent neural network designed to capture long-term dependencies. MLP models have been employed in various domains to capture nonlinear patterns, while LSTM models have demonstrated success in capturing long-term dependencies in sequential data. By comparing against established baselines, it becomes possible to assess whether N-BEATS offer improvements in forecasting accuracy, interpretability, computational efficiency, or other relevant factors. Both models were trained for 2000 epochs using Adam optimizer and MSE as the loss function, and evaluated on training and testing datasets. The baseline models were evaluated by comparing MSE values to assess forecasting accuracy. Lower MSE values indicate more accurate predictions.

Table 3. Comparison of the models on MSE

Model	Yearly	Monthly	Weekly
N-BEATS	116.346	38.229	19.018
LSTM	1.647×10^6	5.353×10^6	1.010×10^7
MLP	1.386×10^6	4.926×10^6	9.828×10^6

A comparison between the MSE scores of the three models has been shown in Table 3. The models, N-BEATS, LSTM, and MLP, were evaluated based on their Mean Squared Error (MSE) values for different time frequencies. The N-BEATS model achieved MSE values of 116.346 for yearly, 38.229 for monthly, and 19.018 for weekly data. In comparison, the LSTM model yielded higher MSE values of 1.647×10^6, 5.353×10^6, and 1.010×10^7 for yearly, monthly, and weekly frequencies, respectively. Similarly, the MLP model had MSE values of 1.386×10^6, 4.926×10^6, and 9.828×10^6 for the corresponding time frequencies. In yearly TAB forecasts, the MLP performed marginally better than LSTM whereas in monthly and weekly forecasts of TAB, LSTM performed better than MLP. These results indicate that the N-BEATS model outperformed both baseline models in terms of forecasting accuracy, as it achieved lower MSE values across all time frequencies.

Our proposed model performed better than LSTM and MLP in wildfire prediction, primarily due to the unique capabilities of the N-BEATS architecture. N-BEATS offers a distinct advantage with its multi-horizon forecasting capability, allowing it to predict future values across multiple time horizons simultaneously. Additionally, N-BEATS is highly adaptable to different types of time series data, requiring minimal manual tuning. This adaptability ensures that N-BEATS can effectively capture complex temporal patterns and non-linear relationships present in wildfire occurrence data without extensive pre-processing or feature engineering. In contrast, the MLP model, despite its ability to learn complex patterns, struggles to capture long-term dependencies and handle noisy data effectively. It relies on the architecture of fully connected layers, which may limit its capacity to model temporal relationships in time series data. MLPs process each input independently, lacking the ability to retain sequential information across time steps. This limitation hinders their performance in tasks like wildfire prediction, where understanding the temporal dynamics and dependencies is crucial.

On the other hand, the LSTM model is specifically designed to capture long-term dependencies in time series data. However, it can encounter issues with vanishing or exploding gradients, particularly when dealing with lengthy sequences. This can hinder its learning process and affect the model's ability to capture intricate temporal patterns effectively. Additionally, LSTM models require more computational resources compared to MLP models due to their recurrent nature and complex architecture.

5. Conclusion and Future Work

This study examined the use of the advanced deep learning-based forecasting model N-BEATS to predict the total area burned by wildfire events at state and country levels in the United States. We also sought to identify spatiotemporal patterns in countrywide wildfire events using kernel density maps. Comparing our technique with the prior works, we find a change from statistical models and ensemble methods towards a more integrated deep learning and spatial analysis methodology. While the prior studies focused on specific regions or employed standard statistical and machine learning techniques (e.g., ARIMA, SVM, Random Forest) for wildfire prediction, our approach employs the N-BEATS model and spatial analysis tools (choropleth, kernel density maps) for countrywide monthly forecasting which exhibited an MSE of 38.2. Our results show that N-BEATS has the potential to be an effective tool for forecasting wildfire activity and that there are distinct spatiotemporal patterns in wildfire occurrence across the United States. These findings have implications for wildfire suppression efforts, as accurate forecasting can help optimise resource allocation and reduce costs. One limitation of this study is that the time series data available was not sufficient to accurately forecast wildfire activity at the state level. While the N-BEATS model exhibits some reliability in predicting the total area burned at country level, the limited size of the data set may have impacted the model's performance at the state level. In the future, it would be beneficial to have access to a larger, comprehensive, and multivariate time series data set to further test the capabilities of forecasting models for predicting wildfire activity at the state level. Additionally, we can utilise other data sources, such as meteorological and topographic data, to enhance the predictive power of the models. Furthermore, the potential of transfer learning and ensemble techniques can be investigated to leverage the strengths of different models for improved wildfire forecasting.

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References

[1] Yajiao Tang, Zhenyu Song, Yulin Zhu, Huaiyu Yuan, Maozhang Hou *et al.* "A survey on machine learning models for financial time series forecasting", *Neurocomputing*, Print ISSN: 0925-2312, Online ISSN: 1872-8286, 1st November 2022, Vol. 512, pp. 363-380, DOI: 10.1016/j.neucom.2022.09.003, Published by Elsevier B.V., Available: https://www.sciencedirect.com/science/article/pii/S092523122201089X.

[2] Bryan Lim and Zohren Stefan, "Time-series forecasting with deep learning: a survey", *Philosophical Transactions of the Royal Society A Mathematical, Physical and Engineering Sciences*, Print ISSN: 1364-503X, 15th February 2021, Vol. 379, No. 2194, pp. 1-13, DOI: 10.1098/rsta.2020.0209, Published by The Royal Society publishing, Available: https://royalsocietypublishing.org/doi/pdf/10.1098/rsta.2020.0209.

[3] Christopher Meek, David M. Chickering and David Heckerman, "Autoregressive tree models for time-series analysis", in *Proceedings of the 2002 SIAM International Conference on Data Mining, Society for Industrial and Applied Mathematics*, 11-13 April 2002, Arlington, USA, ISBN: 0898715172, pp. 229-244, Published by Society for Industrial & Applied Mathematics, Available: https://epubs.siam.org/doi/pdf/10.1137/1.9781611972726.14.

[4] Sima S. Namini, Neda Tavakoli and Namin A. Siami, "A comparison of ARIMA and LSTM in forecasting time series", in *Proceedings of the 2018 17th IEEE international conference on machine learning and applications (ICMLA)*, 17-20 December 2018, Orlando, Florida, USA, Electronic ISBN: 978-1-5386-6805-4, pp. 1394-1401, Published by IEEE, DOI: 10.1109/ICMLA.2018.00227, Available: https://ieeexplore.ieee.org/document/8614252.

[5] Zannatul Ferdoush, Nazifa M. Booshra, Amitabha Chakrabarty and Jia Uddin, "A short-term hybrid forecasting model for time series electrical-load data using random forest and bidirectional long short-term memory", *International Journal of Electrical and Computer Engineering*, 2021, Vol. 11, No. 1, pp. 763-771, Published Institute of Advanced Engineering and Science (IAES), DOI: 10.11591/ijece.v11i1.pp763-771, ISSN 2088-8708, Available: https://ijece.iaescore.com/index.php/IJECE/article/view/22929.

[6] Momotaz Begum, Jahid H. Rony, Md R. Islam and Jia Uddin, "Long-Term Software Fault Prediction Model with Linear Regression and Data Transformation", *Journal of Information Systems and Telecommunication (JIST)*, 20th August 2023, Vol. 3, No. 43, DOI: 10.61186/jist.36585.11.43.222, ISSN: 2322-1437, Published by Academic Center for Education, Culture and research (ACECR), Available: http://jist.ir/Article/36585/FullText.

[7] Boris N. Oreshkin, Dmitri Carpov, Nicolas Chapados and Yoshua Bengio, "N-BEATS: Neural basis expansion analysis for interpretable time series forecasting", in *Proceedings of the International Conference on Learning Representations*, ICLR, 26th April – 1st May 2020, Addis Ababa, Ethiopia, pp. 1-31, Available: http://mapdic.com/upload/2022/07/param-a3aa083f4dc74071814b8986acf28c71.pdf.

[8] Azad Deihim, Eduardo Alonso and Dimitra Apostolopoulou, "STTRE: A Spatio-Temporal Transformer with Relative Embeddings for multivariate time series forecasting", *Neural Networks*, ISSN: 0893-6080, November 2023, Vol. 168, pp. 549-559, Published by Elsevier B.V., DOI: 10.1016/j.neunet.2023.09.039, Available: https://www.sciencedirect.com/science/article/pii/S0893608023005361#b13.

[9] Bryan Lim, Sercan Ö. Arık, Nicolas Loeff and Tomas Pfister, "Temporal fusion transformers for interpretable multi-horizon time series forecasting", *International Journal of Forecasting*, ISSN: 0169-2070, October–December 2021, Vol. 37, No. 4, pp. 1748-1764, Published by Elsevier B.V., DOI: 10.48550/arXiv.1912.09363, Available: https://www.sciencedirect.com/science/article/pii/S0169207021000637.

[10] Ailing Zeng, Muxi Chen, Lei Zhang and Qiang Xu, "Are transformers effective for time series forecasting?", in *Proceedings of the AAAI conference on artificial intelligence*, 7-14 February 2023, Washington, DC, USA, Online ISSN: 2334-0762, Vol. 37, No. 9, pp. 11121-11128, Available: https://ojs.aaai.org/index.php/AAAI/article/view/26317/26089.

[11] Haiganoush K. Preisler and Anthony L. Westerling, "Statistical model for forecasting monthly large wildfire events in western united states", *Journal of Applied Meteorology and Climatology*, ISSN: 1558-8424, 1st July 2007, Vol. 46, No.

7, pp. 1020–1030, Published by American Meteorological Society DOI: 10.1175/JAM2513.1, Available: https://journals.ametsoc.org/view/journals/apme/46/7/jam2513.1.xml.

[12] J. N. S. Rubí and P. R. Gondim, "A performance comparison of machine learning models for wildfire occurrence risk prediction in the Brazilian Federal District region", *Environment Systems and Decisions*, ISSN: 21945411, 28th August 2023, Vol. 2023, pp. 1-18, DOI: 10.1007/s10669-023-09921-2, Published by Springer-Verlag, Germany, Available: https://link.springer.com/article/10.1007/s10669-023-09921-2.

[13] Arip S. Nur, Yong J. Kim, Joon H. Lee and Chang W. Lee, "Spatial Prediction of Wildfire Susceptibility Using Hybrid Machine Learning Models Based on Support Vector Regression in Sydney, Australia", *Remote Sensing*, ISSN: 20724292, 28th January 2023, Vol. 15, No. 3, 760, pp. 1-24, Published by MDPI, DOI: 10.3390/rs15030760, Available: https://www.mdpi.com/2072-4292/15/3/760.

[14] Thai-N. Hoang, Sang Truong and Chris Schmidt, "Wildfire forecasting with satellite images and deep generative model", in *Proceedings of the AAAI 2022 Fall Symposium: The Role of AI in Responding to Climate Challenges*, 17-19 November 2022, Virginia, USA, Vol. v1, pp. 1-9, Available: https://www.climatechange.ai/papers/aaaifss2022/7.

[15] Charles Hernandez, C. Keribin, D. Philippe and S. Turquety, "Statistical modelling of wildfire size and intensity: a step toward meteorological forecasting of summer extreme fire risk", *Annales Geophysicae*, ISSN: 0992-7689, 15th December 2015, Vol. 33, No. 12, pp. 1495–1506, Published by European Geosciences Union, DOI: 10.5194/angeo-33-1495-2015, Available: https://hal.sorbonne-universite.fr/hal-01260501.

[16] Brain Beckage and William J. Platt, "Predicting severe wildfire years in the florida everglades", *Frontiers in Ecology and the Environment*, Print ISSN: 1540-9295, June 2003, Vol. 1, No. 5, pp. 235–239, Published by Wiley, DOI: 10.2307/3868010, Available: https://esajournals.onlinelibrary.wiley.com/doi/abs/10.1890/1540-9295/.

[17] L Gudmundsson, F C Rego, M Rocha and S I Seneviratne, "Predicting above normal wildfire activity in southern europe as a function of meteorological drought", *Environmental Research Letters*, Print ISSN: 1748-9326, 15th August 2014, Vol. 9, No. 8, pp. 1-8, Published by IOP Publishing, DOI: 10.1088/1748-9326/9/8/084008, Available: https://iopscience.iop.org/article/10.1088/1748-9326/9/8/084008.

[18] Harkiran Kaur and Sandeep K. Sood, "Energy-Efficient IoT-Fog-Cloud Architectural Paradigm for Real-Time Wildfire Prediction and Forecasting", *IEEE Systems Journal*, Print ISSN: 19379234, 2nd July 2019, Vol. 14, No. 2, pp. 2003–2011, Published by IEEE, USA, DOI: 10.1109/JSYST.2019.2923635, Available: https://ieeexplore.ieee.org/document/8753728.

[19] Yongjia Song and Yuhang Wang, "Global wildfire outlook forecast with neural networks", *Remote Sensing*, ISNN: 20724292, 9th July 2020, Vol. 12, No. 14, pp. 1-19, Published by MDPI, DOI: 10.3390/rs12142246, Available: https://www.mdpi.com/2072-4292/12/14/2246.

[20] Sibo Cheng, Yufang Jin, Sandy P. Harriso, César Q. Casas, Iain C. Prentice *et al.* "Parameter flexible wildfire prediction using machine learning techniques: Forward and inverse modelling", *Remote Sensing*, ISNN: 20724292, Vol. 14, No. 13, pp. 1-24, 5th July 2022, Published by MDPI, DOI: 10.3390/rs14133228, Available: https://www.mdpi.com/2072-4292/14/13/3228.

[21] Haiganoush K. Preisler, Karin L. Riley, Crystal S. Stonesifer, Dave E. Calkin and Matt Jolly, "Near-term probabilistic forecast of significant wildfire events for the Western United States", *International Journal of Wildland Fire*, ISSN: 14485516, 3rd October 2016, Vol. 25, pp. 1169-1180, Published by CSIRO, DOI: 10.1071/WF16038, Available: https://www.fs.usda.gov/research/treesearch/53305.