Impact of Deforestation and Industrialization on Temperature Trends in India: A Time Series Perspective

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Abstract:

In the global warming scenario, understanding temperature variations and studying them for future predictions is the need of the hour now. Key contributions to rising temperature include deforestation, which reduces carbon absorptions, and industrial urbanisation, which increases greenhouse gas emissions. With the help of statistical techniques, we can address this issue systematically and scientifically. This study analyses temperature fluctuations in India using time series data from 1901 to 2017. Statistical models like ARIMA (Autoregressive Integrated Moving Average Model) and Holt's Exponential Smoothing forecast a gradual temperature increase over time. The ARIMA Model and Holt's Exponential Smoothing forecast suggests that the temperature is expected to gradually rise over time. From 2002 to 2023, India lost 414,000 hectares of humid primary forest, exacerbating environmental challenges. From the past two decades, India's industrial urbanization has been increasing at a rate of 2.76%. In this study, we forecasted next seventeen years (2018-2040) using ARIMA (2,1,2) and Holt's Exponential Smoothing. These insights aim to support policymakers in addressing climate change impacts on ecosystems and human communities.

Keywords: ARIMA, Holt's Exponential Smoothing, Global warming, Temperature variations, Climate change, Deforestation.

Introduction:

Understanding temperature fluctuations is critical in the context of global warming and climate change. The Indian subcontinent, known for its diverse climatic zones, has witnessed significant changes in temperature patterns over the decades. Analysing temperature data can provide valuable insights into these trends, helping policymakers and scientists address the challenges posed by climate variability. Temperature is a crucial climate metric impacting human and natural systems, with global mean surface temperature serving as a key climate change indicator due to its near-linear increase with cumulative greenhouse gas emissions.
Surface temperature drives Earth's energy balance, shaping weather and climate. Rising GHG emissions have significantly warmed the atmosphere, increasing extreme events. Regional temperature changes are critical as warming varies across latitudes. [4,5,17]. Climate change, caused by human activities like industrialization and deforestation, is a global challenge[22]. The Paris Agreement aims to limit warming and promote climate resilience. This review explores socio-scientific impacts, sustainable mitigation strategies, and policy responses [1,19,23]. India's temperature trend has been analysed using structural time-series modeling, incorporating deterministic linear trend, trigonometric seasonality, and stochastic autoregression. Diagnostic checks include residual analysis using autocorrelation functions ACF & PACF [6,13]. Meteorological parameters significantly impact environmental changes

and natural phenomena. Temperature, a key meteorological factor, is widely used to monitor climate fluctuations. Since temperature and solar radiation influence plant growth through their effects on cloud cover and soil moisture, accurate forecasting is crucial to minimize potential damages[15].

Extreme weather events like heat waves, droughts, and heavy rainfall significantly impact human health through direct exposure and socio-economic disruptions. With rising global temperatures, heat waves are projected to become more intense and frequent, posing severe health risks, especially in vulnerable regions like India [8,21]. India's surface temperature has significantly increased since 1980, with urbanization contributing to localized heating. Rising greenhouse gas emissions have led to atmospheric warming, impacting weather and climate. This warming is expected to intensify extreme events like heat waves, droughts, and wildfires[9,12]. The increasing surface temperature disrupts the Earth's energy balance, leading to more frequent and intense extreme weather events [10,11,13,].

This research leverages time series analysis to investigate temperature fluctuations in India using a secondary dataset sourced from the website of Government of India. The study examines long-term trends, seasonal patterns, and anomalies, using statistical techniques to forecast future temperatures.

Related Work:

Many researchers have conducted research on India’s temperature and its significant impact. Revadekar, et.al.[20] suggested that India's temperatures rose significantly between 1986 and 2015, with pre-monsoon seasons showing the greatest warming. Warm extremes increased sharply, and surface air temperatures are projected to rise by up to 4.44°C by 2040–2069 under greenhouse gas scenarios. Bhardwaj, et.al.[16] reviewed that theglobal temperatures have risen by over 1.2°C since the industrial revolution, increasing heatwaves, mortality, and extreme weather. Unequal warming impacts regions differently, with India facing severe heatwaves; over 2°C warming could affect a billion people by 2100.Garg, et.al.[19] studies tell us that high temperatures in India reduce student’s math and reading test scores, with 10 extra days above 29°C lowering scores by 0.03 and 0.02 standard deviations. Social programs like NREGA mitigate these impacts, reducing the effect by 38%.

Rodriguez, et.al.[7] did Indian study from 2001–2013 and found that moderately cold temperatures caused significantly more deaths than extreme heat or cold, with 197,000 fatalities in 2015 linked to stroke, ischemic heart disease, and respiratory disorders. Public health measures must address both moderate cold and extreme heat. Carvalho, et.al. [14] reports us that temperature significantly affects plant metabolism, influencing photosynthesis, membranes, antioxidants, heat shock proteins, and nitric oxide production. This review highlights plant acclimatization to thermal stress and tropical plants resilience to climate change.

S. Bera [2] studied that climate change threatens rainfall patterns, affecting river runoff and water availability. The Ganga River faces seasonal water shortages due to irregular distribution. This study analyses district-level seasonal rainfall trends using Mann-Kendall and Sen's slope methods. Bisai et.al.[7] study examines surface air temperature changes at Midnapore Weather Station, India, from 1941-2010. It identifies 13 abrupt change points, revealing a significant climate shift post-2001, with mean annual temperature dropping from 27.11°C to 25.1°C.

Methodology :

In this paper statistical tools used like ARIMA (p, d, q) model – AutoRegressive Integrated Moving Average and Holt's Exponential Smoothing Model which is popularly used for time series forecasting,

ARIMA (Auto Regressive Integrated Moving Average)Model

The ARIMA model forecasts future values in a time series by capturing dependencies among the observations. It's suitable for stationary and non-stationary data, with the integration part making the series stationary if necessary.An autoregressive integrated moving average (ARIMA) is a generalization of an autoregressive moving average (ARMA) model. ARIMA model is classified as an ARIMA (p, d, q) model, where, p is the number of autoregressive terms, d is the number of non-seasonal differences needed for stationarity and q is the number of moving average terms.

The model can be written as: $(1-B)^d \emptyset(B)X_t = \theta(B)Z_t$

Where, $\emptyset(B) = 1 - \emptyset_1 B - \cdots - \emptyset_p B^p$ is termed as autoregressive polynomial,

$\theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q$ is termed as moving average polynomial, and

Z_t is the white noise process.

Holt's Exponential Smoothing Models

Exponential Smoothing is a family of time series forecasting methods that use weighted averages of past observations to forecast future values. The weights decrease exponentially as observations get older, giving more importance to recent data. These models are widely used due to their simplicity, efficiency, and ability to adapt to various types of data patterns (trend and seasonality). In these data we have used Holts Exponential Smoothing Model (Double Exponential Smoothing)

For a Holts Exponential Smoothing Model, the general formula is:

$L_t = \alpha y_t + (1-\alpha)(L_t - 1 + T_t - 1)$

$T_t = \beta(L_t - 1) + (1-\beta)T_t - 1$

$$\hat{y}_{t+m} = L_t + mT_t$$

Where: L_t: Smoothed level at time t,

T_t: Smoothed trend at time t,

$\hat{y}_{t+m}$: Forecast for mm-steps ahead,

α: Smoothing parameter for level ($0<\alpha\leq1$),

β: Smoothing parameter for trend ($0<\beta\leq1$).

The other tests used are the Augmented Dickey-Fuller (ADF) Test and the KPSS Test (Kwiatkowski-Phillips-Schmidt-Shin Test) that determine the stationarity of the time series, STL Decomposition (Seasonal and Trend decomposition using Loess) that divides the time series into its components, accommodating variations in seasonality and trend over time, the Autocorrelation Function (ACF) which illustrates the similarity between observations in a time series separated by a time lag, and the Partial Autocorrelation Function (PACF) which reveals the correlation between a time series and its own lagged values, after accounting for the effects of intermediate lags.

Figure 1. shows the whole process of analysis, from choosing the goal to doing analysis and reaching to a decision.

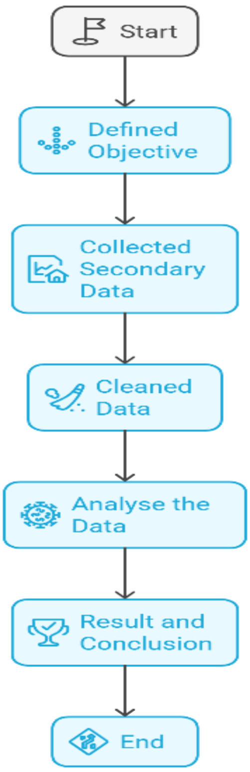

Fig 1. Flowchart of the study

Dataset and Software:

We have collected 3 types of data those are Temperature Data: Provided by Open Government Data (https://www.data.gov.in/catalog/all-india-seasonal-and-annual-minmax-temperature-series), this dataset includes monthly, seasonal, and annual maximum temperature readings for India from 1901 to 2017, all recorded in Celsius. Deforestation Data: This information, obtained from India Deforestation Rates & Statistics https://www.globalforestwatch.org/dashboards/country/IND/), indicates the annual number of trees planted in India and Industrial Data: Sourced from Statista (https://www.statista.com/statistics/271312/urbanization-in-india/) this dataset illustrates the percentage of industrial urbanization from 2013 to 2023.

Python software was used for analysis which included several libraries and packages such as pandas, matplotlib, statsmodels, pmdarimastatsmodels.tsa, statsmodels.graphics.tsaplots, statsmodels.tsa.holtwinters and many more.

Result and Discussion:

The findings of this study are analysed in detail, highlighting the observed trends, underlying causes, and potential consequences of climate change.

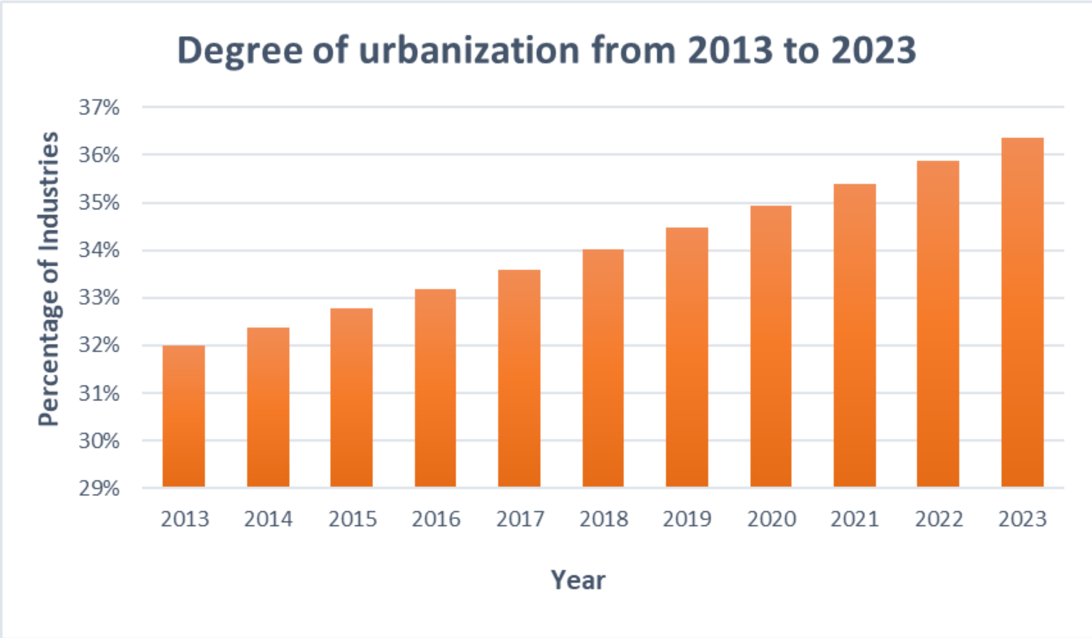

Fig 2. Degree of Urbanization in India

Figure 2. Illustrates that India's industrial urbanization has been increasing at a rate of 2.76% over the past two decades.

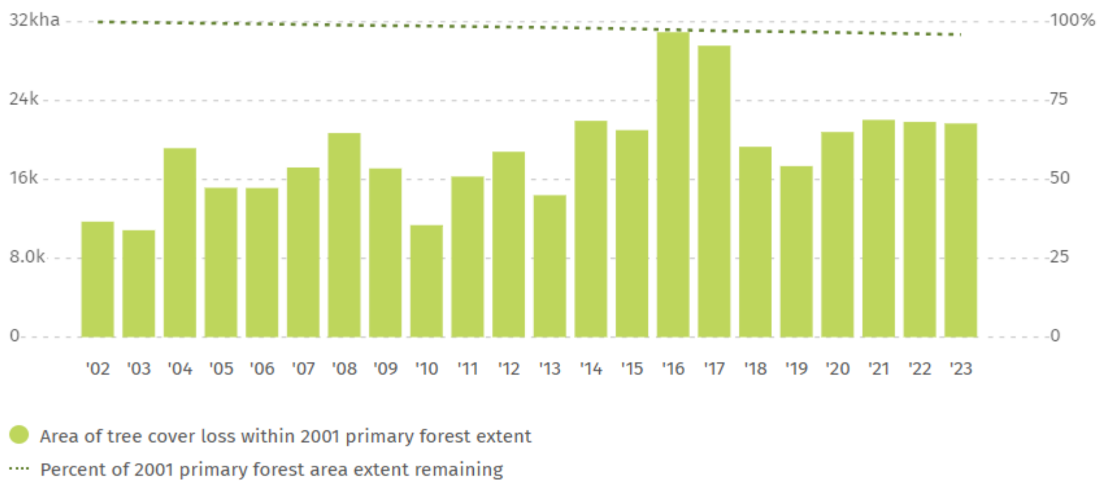

Fig 3. Primary Forest loss in India

Figure 3. shows that From 2002 to 2023, India lost 414 kha of humid primary forest, making up 18% of its total tree cover loss in the same time period. Total area of humid primary forest in India decreased by 4.1% in this time period.

Table 1. Determining the ARIMA (p, d, q) order

ARIMA (p, d, q)	AIC	Time
ARIMA (1,1,1)	64.177	2.19 sec
ARIMA (0,1,0)	91.099	0.06 sec
ARIMA (1,1,0)	83.197	0.05 sec
ARIMA (0,1,1)	70.997	0.08 sec
ARIMA (0,1,0)	89.518	0.03 sec

ARIMA (2,1,1)	62.217	0.16 sec
ARIMA (2,1,0)	77.747	0.08 sec
ARIMA (3,1,1)	63.012	0.29 sec
ARIMA (2,1,2)	**58.416**	**0.48 sec**
ARIMA (1,1,2)	63.818	0.37 sec
ARIMA (3,1,2)	60.429	0.57 sec
ARIMA (2,1,3)	60.231	0.50 sec
ARIMA (1,1,3)	65.871	0.24 sec
ARIMA (3,1,3)	64.584	0.63 sec

Table 1 shows that ARIMA (2,1,2) intercept Total fit time: 6.019 seconds with AIC value 58.416. So, the best ARIMA order is (2, 1, 2).

Table 2. Fitting the ARIMA (2,1,2) model

SARIMAX Results

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Dep. Variable:	ANNUAL	No. Observations:	117
Model:	ARIMA (2, 1, 2)	Log Likelihood	-26.639
Date:	Sun, 19 Jan 2025	AIC	63.277
Time:	09:00:53	BIC	77.045
Sample:	01-01-1901 - 01-01-2017	HQIC	68.866
Covariance Type:	opg		

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	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	1.0305	0.215	4.800	0.000	0.610	1.451
ar.L2	-0.5224	0.141	-3.699	0.000	-0.799	-0.246
ma.L1	-1.5905	0.212	-7.505	0.000	-2.006	-1.175
ma.L2	0.7174	0.192	3.737	0.000	0.341	1.094
sigma2	0.0914	0.007	13.731	0.000	0.078	0.104

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Ljung-Box (L1) (Q):	0.21	Jarque-Bera (JB):	234.99
Prob(Q):	0.65	Prob(JB):	0.00
Heteroskedasticity (H):	2.72	Skew:	1.49
Prob(H) (two-sided):	0.00	Kurtosis:	9.31

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The best model drawn from Table 2 is fitted and it's results are shown in Table 3 i.e the forecasted temperature for the years 2017 to 2040 is represented. The ARIMA(2,1,2) model is fitted to a time series with 117 observations, showing significant AR terms and MA terms.

Table.3 ARIMA Forecasted values

Year	Forecast	Lower Bound	Upper Bound
2018	30.326226	29.733721	30.91873
2019	29.836545	29.189219	30.483872
2020	29.9033	29.255064	30.551536
2021	30.227896	29.579154	30.876638
2022	30.527527	29.878051	31.177002
2023	30.666735	30.0062	31.327269
2024	30.653667	29.968221	31.339113
2025	30.567479	29.853167	31.281791
2026	30.485488	29.747185	31.22379
2027	30.446017	29.690031	31.202004
2028	30.448175	29.678372	31.217977
2029	30.471016	29.688607	31.253426
2030	30.493428	29.697968	31.288889

2031	30.504592	29.695113	31.314071
2032	30.504389	29.680242	31.328535
2033	30.498347	29.6595	31.337194
2034	30.492227	29.639098	31.345356
2035	30.489077	29.622212	31.355942
2036	30.489027	29.608872	31.369183
2037	30.490622	29.59745	31.383794
2038	30.492291	29.586253	31.398329
2039	30.493178	29.574377	31.41198
2040	30.493221	29.56177	31.424671

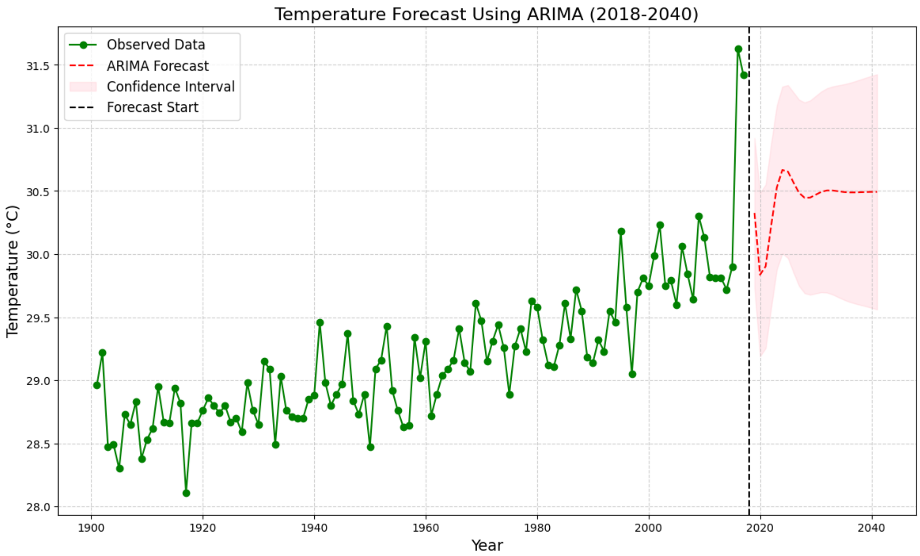

Fig 5. Temperature Forecast using ARIMA

In Figure 5, the forecasted values obtained from ARIMA (2,1,2) model are depicted.

Table 4. Temperature forecast of Holt's Exponential Smoothing

Year	Forecast	Lower Bound	Upper Bound
2018	30.334763	29.723135	30.946391
2019	30.376675	29.765048	30.988303
2020	30.418588	29.806960	31.030215
2021	30.460500	29.848872	31.072128
2022	30.502412	29.890784	31.114040
2023	30.544324	29.932697	31.155952
2024	30.586237	29.974609	31.197864
2025	30.628149	30.016521	31.239777

2026	30.670061	30.058433	31.281689
2027	30.711973	30.100346	31.323601
2028	30.753886	30.142258	31.365513
2029	30.795798	30.184170	31.407426
2030	30.837710	30.226082	31.449338
2031	30.879622	30.267995	31.491250
2032	30.921535	30.309907	31.533162
2033	30.963447	30.351819	31.575075
2034	31.005359	30.393731	31.616987
2035	31.047271	30.435644	31.658899
2036	31.089184	30.477556	31.700811
2037	31.131096	30.519468	31.742724
2038	31.173008	30.561380	31.784636
2039	31.214920	30.603293	31.826548
2040	31.256832	30.645205	31.868460

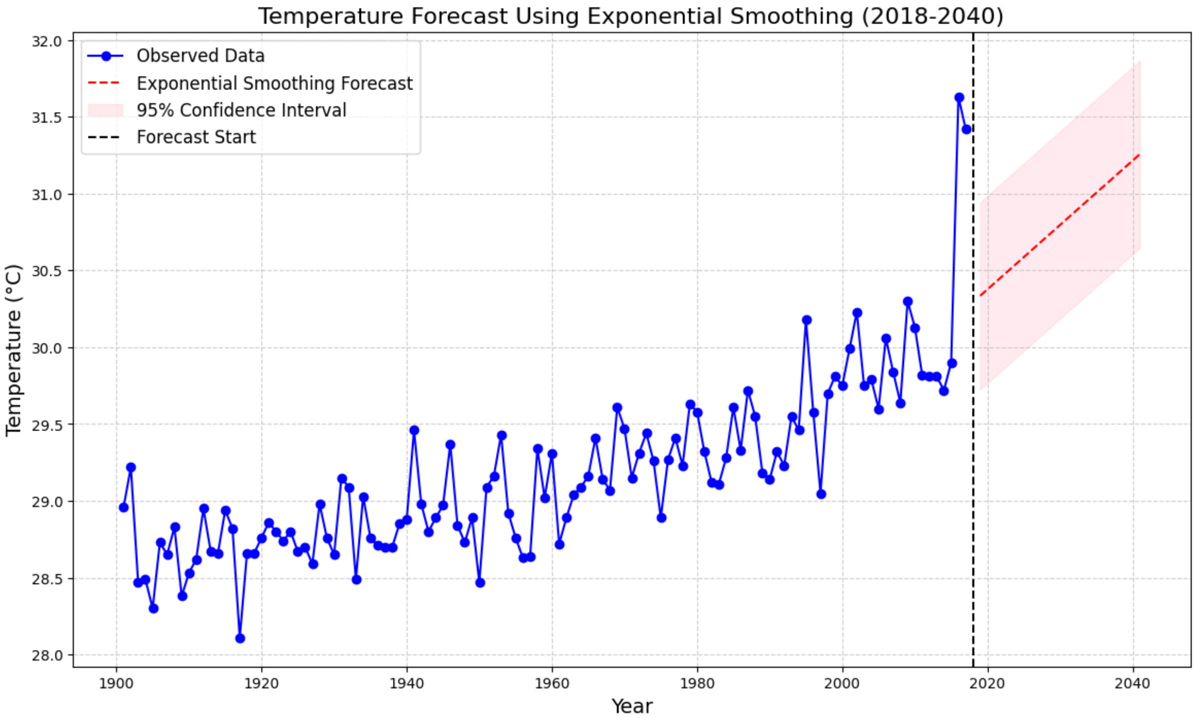

Fig 6. Temperature Forecast (2018-2040) using Exponential Smoothing

In Figure 6, we have forecasted the temperature using Exponential Smoothing Model.

Conclusion:

The ARIMA model and exponential smoothing forecast indicate a gradual rise in temperature over time. The primary drivers of these fluctuations are deforestation and industrial urbanization. Forests serve as crucial carbon sinks, absorbing carbon dioxide from the atmosphere. However, widespread deforestation significantly reduces this capacity, leading to an accumulation of greenhouse gases and subsequent temperature variations. Rapid industrialization further exacerbates this issue, contributing to extreme weather patterns, biodiversity loss, and challenges for agriculture. To mitigate these effects, several measures are proposed, including transitioning to renewable energy sources such as solar, wind, and hydroelectric power. Expanding reforestation programs, particularly focusing on native species, can help restore ecological balance. Additionally, offering incentives such as subsidies and tax benefits to industries that adopt sustainable practices and green technologies can further support climate action. In conclusion, human activities play a crucial role in temperature fluctuations across India. By analysing historical data and leveraging predictive models, we can better prepare for future climate changes and implement effective mitigation strategies. The key takeaway remains clear: ***Temperature Swings, Nature's Warnings – Pay Attention***.

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