Results from Weather Modelling

July 2024

Trends in Maximum and Minimum Temperature

Literature Review

Roy and Balling Jr. use reanalysis data from the CRU and found no trends from 1901 - 1931. In the analysis period from 1932 - 2002, they found an increase in the minimum temperatures in the South of India, during both the summer and winter. They also found a negative relationship between cloud cover and temperature as expected[12]. Kumar et. al. use IMD data until 1987, finding an increase in maximum and mean temperatures, with no trends in minimum temperatures. They also find the trend is consistent across different heights and even urban and rural stations[6]. In a following paper, Kumar and Kothawale used data from IMD from 1901 to 2003, and found that the minimum temperatures are almost trendless across the entire period, but maximum temperatures have seen a rise. Minmum temperatures do see a sharp rise after 1955, but that becomes more gradual starting in 1970[5].

Much literature in analysing trends for temperatures are focused on a number of indices outlined by the Expert Team of Climate on Climate Change Detection and Indices(ETCCDI). This is a set of 16 temperature-related and 11 precipitation related indices used to track climate change. A full list is attached in the Appendix. Rehana et. al. upsampled the $1^{\circ}\times 1^{\circ}$IMD temperature dataset to $0.25^{\circ}\times 0.25^{\circ}$using billinear interpolation, and used Sen's slope estimator alongside the mann-kendall test to look for trends. They found significant warming trends in TXx, TNx, TX90p and TN90p in over 40% of the area all over India. The spatial averages for warming-related indices also showed increasing trends[10]. Kumar et. al. used $1^{\circ}\times 1^{\circ}$IMD data until 2013, finding limited significant trends in the days above the 95th percentile and below the 5th percentile for daily maxima and daily minima respectively[7]. Guntu and Agarwal found increasing trends in temperatures across the countries in the same IMD dataset from 1951-2019. They also found increasing trends in hot and dry events (Temperature > 75th percentile and Rainfall < 25th percentile) and a decrease in cold and wet events (Temperature < 25th percentile and Rainfall > 75th percentile)[3]. Rohini et. al. looked at two new indicators against the period from 1971-2000. The indices are the 90th percentile of maximum temperatures based on 5 day window for each day, as well as the excessive heat factor. They found increasing trends in the frequency, mean duration and total duration of heat waves over Northwestern india, and no significant trends elsewhere. On account of the increase in minimum temperatures increasing in India, they also found the EHF showed a larger magnitude than the 90th percentile for max temperatures, since it is also influenced by minimum temperatures[11].

Dataset

The data used is 1°× 1°daily data from IMD for the years 1951-2023. In specified places, 0.5°× 0.5°daily data has been used after downsampling it to a 1°× 1°resolution. Grids with any missing values were dropped. Both were also spatially averaged inside the borders of India to study the all India trends

Results

Grid-Wise Trends

The trends for the average values for the daily minimum temperatures and maximum temperatures were calculated, and a linear trend line was fit to them. These results are presented in Figure 1. Both extremes, when averaged over the entire year, show increasing trends almost everywhere, save for certain pockets near the East Coast showing a falling trend for minima and parts of North India showing a falling trend for maxima.

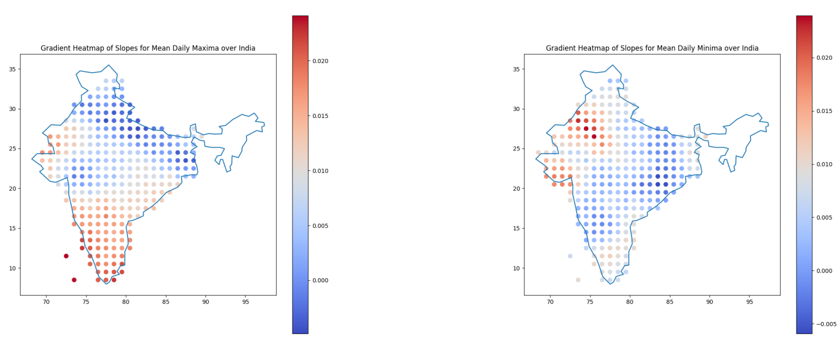

Figure 1: Figure 2: Heatmaps for grid-wise trends in the yearly averages of daily maximum(left) and minimum(right) temperatures

All India Trends

The spatial averages show increasing trends in mean daily maxima, as well as mean daily minima. While the trend in maxima looks consistent throughout the period of study. The minimum temperature starts of almost as high as it's current value, which is consistent with the spike mentioned in [5]. The minimum drops sharply around 1960, and then sees a more gradual rise following that. The presence of significant trends were checked using the non-parametric Mann-Kendall Test, which showed significant trends for both series.

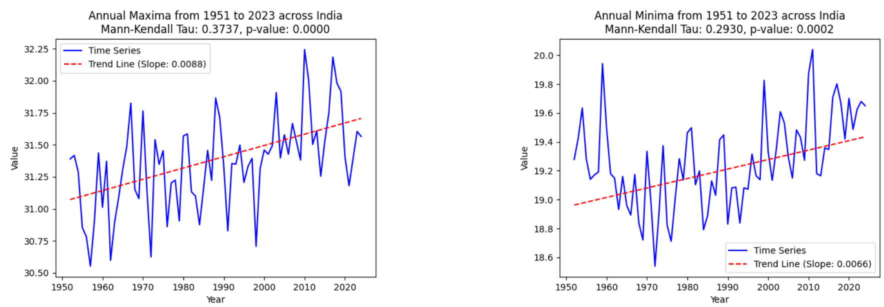

Figure 2: Figure 1: Time series for all India trends in the yearly averages of daily maximum(left) and minimum(right) temperatures

Hot Spells

We further wanted to see if there has been an appreciable increase in the number of hot spells. We defined a hot spell as a continuous period where the maximum temperature remains above a certain threshold. We looked at these values for only the summer months, and the results can be found below. North and East India show small increasing trends, and rarely even falling trends, with the rest of the country showing increasing trends. This approach is different from existing approaches in literature, as indices such as the WSDI look at exceedences over the day-wise thresholds, which could remove the effect of any seasonality inside the summer months.

Predicting Temperatures using Machine Learning

Literature Review

Compared to precipitation, there is less work on temperature prediction using deep learning. Gong et. al. find that Conv-LSTMs are outperformed by their modified GAN architecture. The models were trained on ERA5 reanalysis data for Europe, at a 0.3°resolution, using 12 hours of data to predict the next 12 hours. It is also worth noting the training data was only 13 years [2]. Another paper uses additional variables (accumulated precipitation, wind speed, average wind direction and humidity) to predict temperatures in Korea using the informer architecture. This was done using 3 years and 3 months of data.

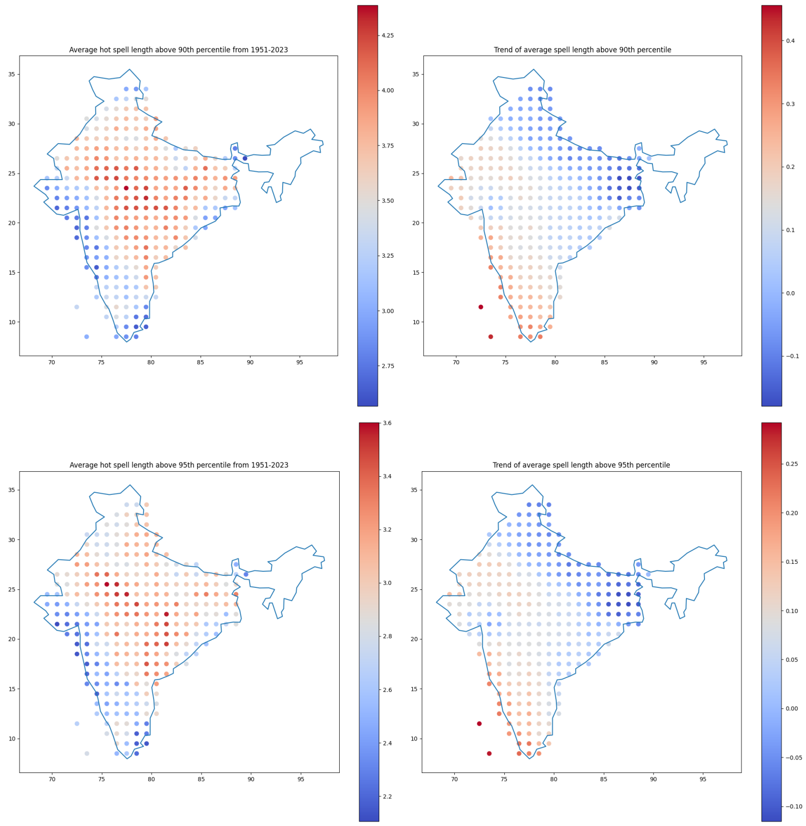

Figure 3: Figure 3: Heatmap showing the grid-wise trend in average length of exceedences above the 90th(top) and 95th(bottom) percentiles. The left image is the average spell length, and the right image shows the slope of the trend line

They propose a hybrid model that uses NWP forecast images alongside observed data.[4]. Work in climate forecasting has either looked at precipitation forecasts, or looked at forecasts of multiple variables, see [1]. This has been helped by datasets such as Weatherbench[9], which cleans ERA5 reanalysis and prepares it for use in training and testing machine learning models.

Training Details

The model tried was a simple one dimensional convolutional neural network, aiming to predict temperature for the next 3 days when given temperatures for the past 15 days. Additionally, this model made use of the starting and ending timepoints, by feeding them into a linear embedding layer. This output was concatenated with the output from the CNN and fed to a feedforward network.

The data was split into a training set from 1951-2008, validation set from 2009-2013 and test set from 2014-2023. Missing values were left as is at 99

The models were trained on different objectives, namely mean-squared error, a peak biased loss function, and a scaled power of the MAE function, which can be written as

$$MSE = \sum_i (\hat{y_i} - y_i)^2$$

$$MAE_{PB} = \sum_i \mathbb{I}_{\hat{y_i} > y_i}(\hat{y_i} - y_i) + \mathbb{I}_{\hat{y_i} < y_i}(y_i - \hat{y_i})^{1.5}$$

$$MAE_{mod} = \sum_i |\hat{y_i} - y_i|^{1.5}$$

The MSE losses for grids containing certain key cities across different numbers of epochs are presented here. Losses do not see much change across throughout, and an interesting pattern is that cities in North India have higher losses than the others. This might be because they register steeper day to day jumps and drops compared to cities in Central or Southern India. This is supported by the fact that coastal cities show the smallest errors, which are known to have small variations in their temperature year-round.

Losses cannot be compared across different loss functions, instead we present the forecasts from one, two and three days visualised against the groundtruth values for different training schemes here. The peak bias seems to slightly outperform vanilla MSE, as well as the modified MAE function.

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Table 1: MSE after training for different numbers of epochs across grids containing certain key cities

	14	**28**	**42**	**56**	**70**	**84**	**98**
Bangalore	1.6991	1.6068	1.6097	1.5908	1.6066	1.7188	1.5878
Bhopal	3.6220	3.4780	3.3169	3.3849	3.4340	3.4581	3.3934
Chennai	1.8620	1.7718	1.8191	1.7546	1.7754	1.9349	1.7749
Delhi	4.8773	4.6003	4.5398	4.5873	4.6334	4.5570	4.5620
Hyderabad	2.7878	2.5732	2.5574	2.5555	2.6155	2.7012	2.5598
Jaipur	4.9618	4.7662	4.6610	4.7119	4.7607	4.7461	4.7071
Kanpur	4.4341	4.1718	4.1059	4.1535	4.2057	4.2247	4.1510
Kolkata	2.6293	2.5740	2.5226	2.4944	2.5473	2.6041	2.4939
Lucknow	4.0626	3.7895	3.7463	3.7914	3.8403	3.8604	3.7708

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Table 1: MSE after training for different numbers of epochs across grids containing certain key cities (Continued)

	14	**28**	**42**	**56**	**70**	**84**	**98**
Mumbai	1.6315	1.5035	1.4877	1.5083	1.5289	1.6439	1.4987
Nagpur	3.3329	3.1410	3.0257	3.0780	3.1284	3.1555	3.0508
Srinagar	5.1299	4.9299	4.8879	5.0570	5.1233	5.1099	4.9724

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Appendix

Table 2: ETCCDI temperature indices. TN denotes daily minimum, TX denotes daily maximum and TG denotes daily mean ($\frac{\text{TX} + \text{TN}}{2}$) [8]

Index	**Description**
Frost Days (FD)	# days where TN < 0°C
Summer Days (SU)	# days where TX > 25°C
Icing Days (ID)	# days where TX < 0°C
Tropical Nights (TR)	# days where TN > 25°C
Growing Season Length (GSL)	# days between the first six day spell with TG > 5°C and the first six day spell with TG < 5°C in a calendar year
TXn	Smallest TX in a specified period
TXx	Largest TX in a specified period
TNn	Smallest TN in a specified period
TNx	Largest TN in a specified period
TN10p	% of TN < 10th percentile for TN on a given day with respect to a 30 year period, fixed from 1961-1990
TX10p	% of TX < 10th percentile for TX on a given day with respect to a 30 year period, fixed from 1961-1990

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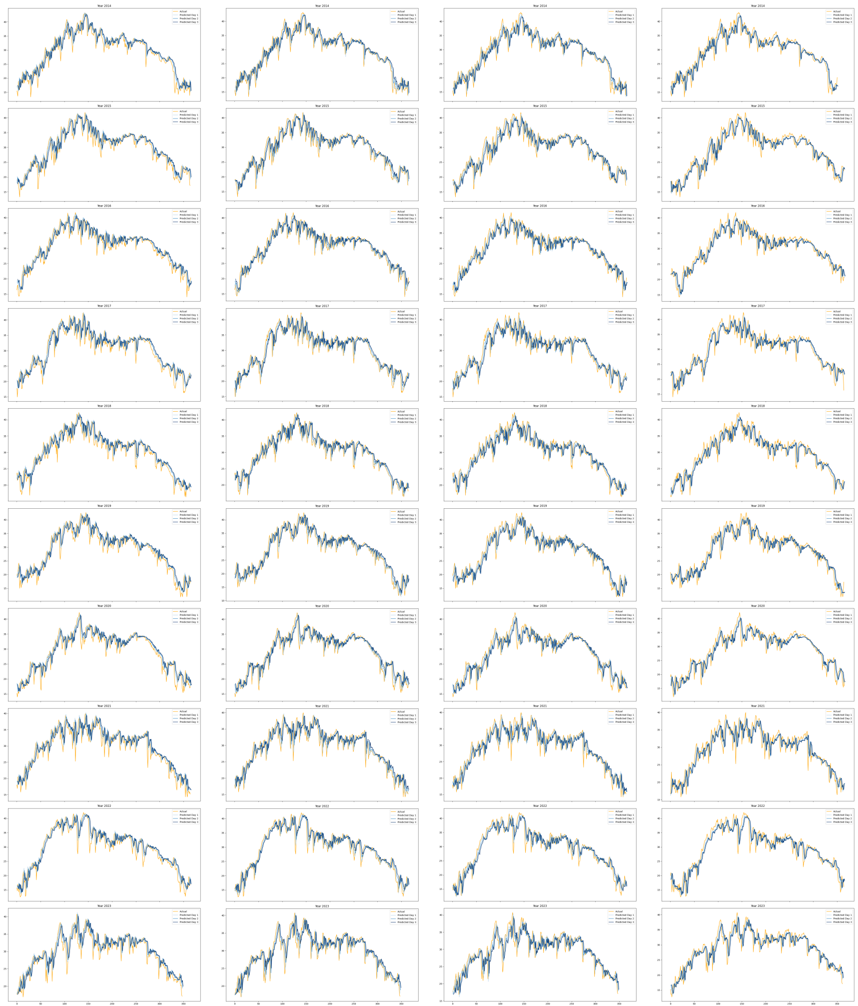
Table 2: ETCCDI temperature indices. TN denotes daily minimum, TX denotes daily maximum and TG denotes daily mean ($\frac{\mathrm{TX} + \mathrm{TN}}{2}$) [8] (Continued)

Index	**Description**
TN90p	% of TN > 90th percentile for TN on a given day with respect to a 30 year period, fixed from 1961-1990
TX90p	% of TX > 90th percentile for TX on a given day with respect to a 30 year period, fixed from 1961-1990
Cold Spell Duration Index (CSDI)	# of consecutive six day spells of TN $\leq$ 10th percentile for some normal period
WSDI	# of consecutive six day spells of TX $\geq$ 90th percentile for some normal period
Diurnal Temperature Range (DTR)	Average difference between maximum and minimum temperatures for a given period ($\frac{\sum \mathrm{TX}\text{ - }\mathrm{TN}}{n}$)



(a) MSE, 20 (b) $PB{-}MAE$, 20 (c) MAE_{mod}, 20 (d) MSE, 100

Figure 4: Visualised Predictions for all 3 days on the test set for the grid (29.5, 77.5) which contains Delhi. The captions specify loss function(epochs trained for)