



Functional Data Analysis of Weather Data

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Table of Contents

- 1 Recap: Data, Smoothing, and Initial FPCA
- PCA on Yearly Data
- Clustering of Cities
- Significance of Cluster Differences
- Conclusion

Recap: Data and Smoothing

• **Data:** Hourly temperature data (*tempC*) for 8 Indian cities (2011-2018).

• Preprocessing:

• Averaged multi-year temperatures for each city, day of year, and hour of day, creating an average annual temperature surface (365 days \times 24 hours) per city.

Bivariate Smoothing:

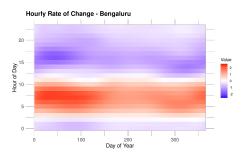
- Day dimension: B-spline basis (12 basis functions).
- Hour dimension: Fourier basis (11 basis functions, 5 harmonics + intercept).
- Optimal smoothing parameters ($\lambda_s = 0.001$, $\lambda_t = 10^{-5}$) selected via Generalized Cross-Validation (GCV).
- Result: Smoothed bivariate functional data object for each city's average temperature surface. MAE $\approx 0.51^{\circ}C$.



Recap: Temperature Derivatives

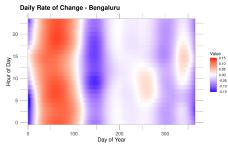
Example: Dynamics for Bengaluru

Hourly Rate of Change $\left(\frac{\partial T}{\partial hour}\right)$



Rate of temperature change throughout the day, across the year. Red: warming, Blue: cooling.

Daily Rate of Change $\left(\frac{\partial T}{\partial day}\right)$



Rate of temperature change from one day to the next, at different hours. Red: inter-day warming, Blue: inter-day cooling.



Recap: Initial FPCA

Initial FPCA (on City Averages):

- Performed on the coefficients of the smoothed city-average surfaces.
- Revealed primary modes of variation in temperature patterns across cities.
- PC1 captured 77.0% of the variance, mostly the yearly seasonal cycle.
- PC2 captured 12.3% of the variance, mostly the inter-day variability.

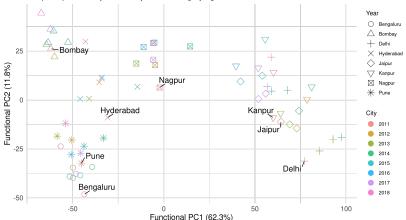
Today's Focus: Deeper analysis building upon these smoothed functional representations.

FPCA on Yearly Temperature Surfaces

FPCA performed for each city and each year (2011-2018).

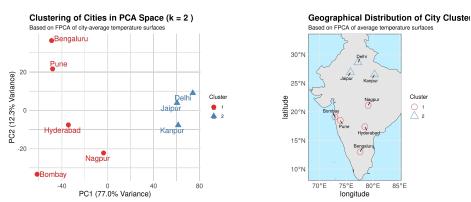
FPCA Scores of Yearly Temperature Surfaces

Each point represents one year for one city. Smoothed using city-avg lambdas.



Clustering Cities by Average Temperature Profiles

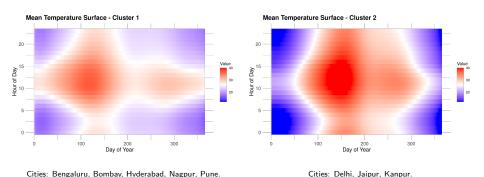
Hierarchical clustering (k = 2) on PC1, PC2, PC3 scores of the 8 city-average temperature surfaces.



Identified Clusters: Southern/Central vs Northern/Inland cities.

FDA of Weather Data p. 7 of 11

Mean Temperature Surfaces per Cluster



Observations:

- Cluster 1 (Southern/Central): Warmer winters, less extreme summer highs, temperature dip during monsoon season.
- Cluster 2 (Northern/Inland): More pronounced seasonality with colder winters and hotter summers.

Pointwise FANOVA for *Temperature* ~ *Cluster*

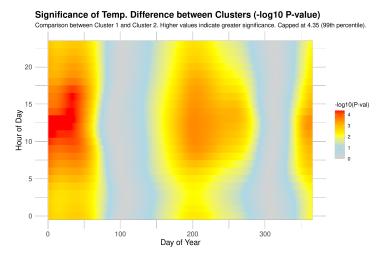


Figure: Higher values indicate stronger statistical significance of temperature difference between clusters.

FDA of Weather Data p. 9 of 11

Conclusions and Future Work

Key Findings:

- Derivatives & Covariance: Revealed intra-day and inter-day temperature dynamics and relationships.
- Yearly FPCA: Quantified inter-annual variability and highlighted distinct city-level climatic trajectories over the years.
- **Clustering:** Grouped cities into clusters based on their annual temperature surfaces.
 - Southern/Central cities with milder variations.
 - Northern cities with more extreme seasonal variations.
- Pointwise FANOVA: Confirmed statistically significant differences in temperature patterns between clusters, particularly during winter and peak summer daytimes.

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Potential Future Work:

- Functional regression models (e.g., predicting energy demand).
- Anomaly detection for unusual yearly temperature patterns.

A I Smoliakov VII MIE 2025–05–27 11

Thank You!

Thank you for your attention!