Indian Institute of Science Education and Research, Pune

Semester Project Report

Spatio-Temporal Clustering of Heat Waves over South and Southeast Asia (1979–2018)

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April 21, 2025

Acknowledgements

I would like to extend my deepest gratitude to my supervisor, **Dr. Bedartha Goswami**, for his invaluable guidance, unwavering support, and constructive feedback throughout the course of this project. His expertise and encouragement have been instrumental in shaping the direction and outcome of this work.

I am sincerely thankful to the faculty and staff at **IISER Pune** for fostering a stimulating academic environment and providing the resources necessary for my research. Their dedication to excellence has been a constant source of inspiration.

A heartfelt thanks to my friends and colleagues for their camaraderie and encouragement during this journey. I am especially grateful to those who took the time to review and provide feedback on my work—their insights have been greatly appreciated.

Finally, I owe my deepest gratitude to my family for their unwavering support, patience, and motivation throughout this endeavor. This work would not have been possible without their constant encouragement and belief in me.

Abstract

This project explores the **spatio-temporal patterns of heat waves** across South and Southeast Asia from 1979 to 2018, employing advanced clustering algorithms to analyze these extreme events. Heat waves are defined as spatio-temporal phenomena, detected using a percentile-based daily threshold and linked through a neighbor graph to form cohesive events.

Temporal clustering, implemented via **K-means** on the mean day-of-year, categorizes heat waves into distinct seasonal families. Spatial clustering, using **UPGMA** based on overlap strength, identifies geographic hotspots. The analysis reveals clear seasonal modes and regional clusters, providing a robust framework for understanding the dynamics of heat waves and their impacts on climate systems.

The findings offer valuable insights into the temporal evolution and spatial distribution of heat waves, paving the way for future studies on their influence on vegetation, ecosystems, and climate dynamics. This framework also facilitates the integration of additional analyses, such as correlations with rainfall and vegetation indices, to further enhance our understanding of these extreme events.

Contents

1 Introduction

1.1 Context & Motivation

The increasing frequency and intensity of heat waves, driven by climate change, pose significant challenges to human health, agriculture, and ecosystems. These extreme temperature events have far-reaching consequences, particularly in vulnerable regions, where they disrupt livelihoods, threaten food security, and strain natural ecosystems. Understanding the patterns and characteristics of heat waves is crucial for mitigating their impacts and developing effective adaptation strategies. For example, the 2015 heat wave in India caused thousands of fatalities and widespread crop failures, while the 2019 heat wave in Southeast Asia led to water shortages and significant damage to biodiversity. Such events highlight the urgent need to understand and mitigate the impacts of extreme heat in South and Southeast Asia, a region particularly vulnerable to climate extremes.

1.2 Problem Statement

Despite the growing urgency to address heat waves, there is a lack of comprehensive analysis of their spatio-temporal patterns in the region. Existing studies often overlook the interconnected nature of heat waves as phenomena that evolve across both space and time, limiting our ability to fully understand their behavior and impacts.

1.3 Objectives

This study aims to:

1. Define heat waves as spatio-temporal phenomena, capturing their dynamic nature across both dimensions.

2. Cluster heat wave events into meaningful seasonal families and geographic groups, providing insights into their temporal evolution and spatial distribution.

3. Propose a framework for (future) assessments of their influence on climate dynamics and vegetation.

2 Background

2.1 Heat Wave Definition and Measurements

Heat waves are defined and measured using various definitions, such as maximum, mean, or minimum temperatures, often relying on absolute or percentile-based thresholds. Advanced methods consider heat waves as spatio-temporal events spanning multiple grid points. The Heat Wave Magnitude Index Daily (HWMId) is a popular metric combining intensity, duration, and spatial extent but may underestimate winter heat waves.

2.2 Physical Causes of Heat Waves in South and Southeast Asia

Heat waves in South and Southeast Asia are driven by rising mean temperatures due to greenhouse gas emissions. Events like the 2015 Indian heat wave are linked to high-pressure systems that block wind flow, suppress rainfall, and create stagnant weather patterns.

Land-atmosphere feedback, such as low soil moisture reducing latent heat release, amplifies heat wave intensity and duration. Large-scale climate patterns like the Indian Ocean Dipole (IOD) and El Niño-Southern Oscillation (ENSO) further contribute by reducing rainfall and increasing temperatures.

Rossby waves and jet stream anomalies also play a role in prolonging heat waves. While progress has been made, further research is needed to better understand these drivers and improve forecasting.

2.3 Deep Graphs Framework

The Deep Graphs framework is a versatile tool for analyzing large and complex datasets. A graph G is defined as:

$$G = (V, E)$$

where: - V: Represents the set of **nodes** (vertices). Each node can have multiple features, such as temperature, location, time, etc. - E: Represents the set of **edges** (relationships between nodes). Edges can also have features, such as strength or a boolean value indicating connectivity.

The Deep Graphs Python module enables users to filter, partition, and analyze graphs, making it easier to uncover meaningful patterns and relationships in the data [1].

In this project: - **Nodes (V)**: Represent extreme heat days at specific grid cells, with features such as temperature, latitude, longitude, time, and magnitude. - **Edges (E)**: Represent relationships between neighboring nodes, such as spatial or temporal proximity. - **Supernodes**: Groups of connected nodes that represent heat waves. Supernodes have features like the Heat Wave Magnitude Index Daily (HWMId), mean day of the year, and average location.

The Deep Graphs framework has been successfully applied in various studies, including rainfall pattern analysis [1, 2] and spatio-temporal wildfire patterns in the Amazon.

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2.4 K-Means Clustering

K-Means is an unsupervised clustering algorithm that partitions data into K clusters by minimizing the variance within each cluster. It is based on Lloyd's algorithm and follows these steps:

1. **Initialization**: Randomly select K cluster centroids. 2. **Assignment Phase**: Assign each data point x_i to the nearest cluster C_k based on the Euclidean distance:

$$d(x_i, C_k) = \sqrt{\sum_{j=1}^{n}(x_{ij} - \mu_{kj})^2}$$

where μ_{kj} is the centroid of cluster C_k. 3. **Update Phase**: Recalculate the centroid of each cluster as the mean of all points in the cluster:

$$\mu_k = \frac{1}{|C_k|} \sum_{x_i \in C_k} x_i$$

4. **Iteration**: Repeat steps 2 and 3 until the cluster assignments stabilize.

Advantages: - Computationally efficient for large datasets. - Simple and easy to implement.

Limitations: - Requires the number of clusters (K) to be predefined. - Sensitive to the initial placement of centroids, which can lead to suboptimal solutions.

In this project, K-Means is used to group heat waves into seasonal families based on their temporal characteristics, such as the day of the year.

2.5 UPGMA Clustering

UPGMA (Unweighted Pair Group Method with Arithmetic Mean) is a hierarchical agglomerative clustering method. Unlike K-Means, it does not require the number of clusters to be predefined.

Algorithm Steps: 1. Start with each data point as its own cluster. 2. Compute the pairwise distance between clusters using a distance matrix. 3. Merge the two closest clusters into a single cluster. The distance between two clusters C_i and C_j is calculated as:

$$d(C_i, C_j) = \frac{1}{|C_i| \cdot |C_j|} \sum_{x \in C_i} \sum_{y \in C_j} d(x, y)$$

where $|C_i|$ and $|C_j|$ are the sizes of clusters C_i and C_j, respectively. 4. Update the distance matrix and repeat until all data points are merged into one cluster. 5. The result is a dendrogram, which visually represents the hierarchical relationships between clusters.

Advantages: - Does not require a predefined number of clusters. - Useful for identifying hierarchical relationships in data.

Limitations: - Once clusters are merged, they cannot be split later, even if a better solution exists.

In this project, UPGMA is used to group heat waves spatially, identifying clusters based on their geographic overlap and proximity.

2.6 Summary

The combination of the Deep Graphs framework, K-Means clustering, and UPGMA clustering provides a robust computational approach for analyzing spatio-temporal patterns of heat waves. - **Deep Graphs**: Models heat waves as spatio-temporal phenomena with nodes and edges. - **K-Means**: Groups heat waves into seasonal clusters based on temporal characteristics. - **UPGMA**: Identifies spatial clusters of heat waves based on geographic proximity.

These methods enable a comprehensive analysis of heat wave patterns, offering insights into their temporal and spatial dynamics.

3 Data and Methods

3.1 Temperature Data

The temperature data used in this analysis was obtained from the ERA5 reanalysis dataset, provided by the Copernicus Climate Data Store. The dataset includes 2-meter land temperature data with a spatial resolution of $1° \times 1°$ and 61×101 pixels. Daily temperature data for the years 1979–2018 was retrieved, and daily maximum temperatures were calculated. The study region spans East 135, West 45, North -15, South 35.

To simplify the analysis, temperature values were converted from Kelvin to Celsius by subtracting 273.15, and the 366th day of leap years was removed.

3.2 Definition of Heat Waves

To define heat waves, a spatio-temporal and threshold-based approach was adopted, following the methodology proposed by Russo et al. [12] and referenced in [Thesis, Julia]. A location-specific daily threshold was calculated based on the 99th percentile of a 30-day rolling window ($+15$ and -15 days) around the day of interest to reduce anomalies in the temperature data. The threshold for a given day (d) and grid cell (g) is defined as:

$$A_{d,g} = \text{99th percentile of maximum temperature values within a 30-day window (1979–2018)}$$

If the daily maximum temperature at a grid cell exceeds this threshold, it is classified as an extreme heat event.

In a three-dimensional coordinate system (longitude, latitude, and time), each extreme heat event can have up to 26 neighboring events: 8 in the same time slice, and 9 each in the preceding and following time slices. A heat wave is defined as a connected group of these neighboring extreme heat events.

To focus on significant heat waves, the following criteria were applied: 1. The event must last for at least three consecutive days. 2. The event must cover at least 100 unique grid cells.

This spatio-temporal definition ensures that only impactful and widespread heat waves are identified for further analysis.

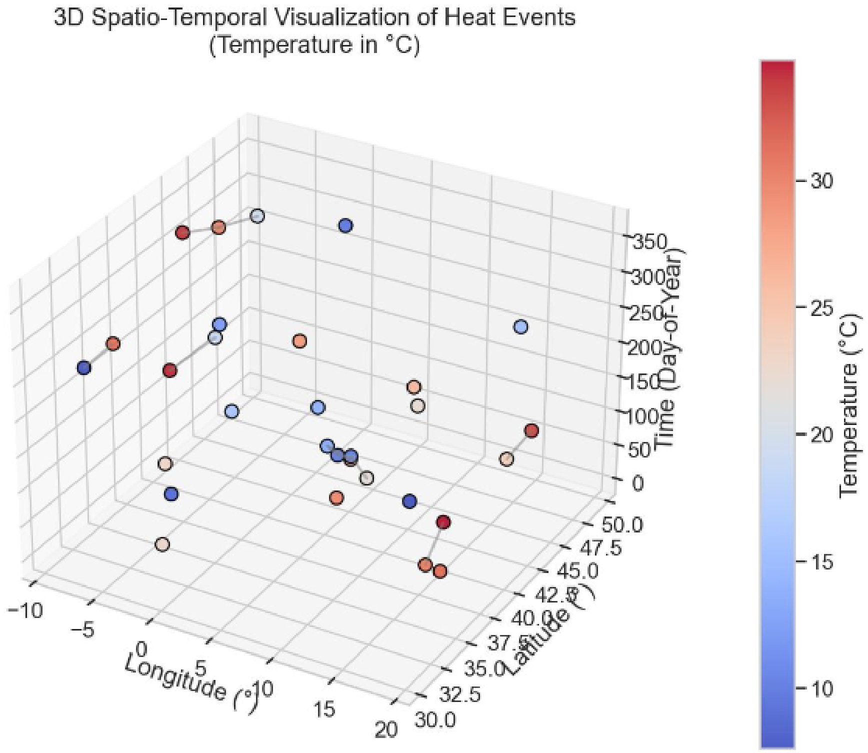


Figure 1: Illustration of a heatwave in 3D space. The figure represents the spatio-temporal extent of a heatwave, with dimensions of longitude, latitude, and time.

3.3 Spatial and Temporal Clustering of Heat Waves

The clustering of heat waves was conducted in two distinct steps: temporal clustering and spatial clustering, each tailored to address specific characteristics of heat waves.

Temporal clustering was performed using the K-Means algorithm. To account for the circular nature of the calendar year, the mean day of the year (DOY) for each heat wave was transformed into circular coordinates using the following equations:

$$\cos(\text{DOY}) = \cos\left(\frac{2\pi \times \text{DOY}}{365}\right), \quad \sin(\text{DOY}) = \sin\left(\frac{2\pi \times \text{DOY}}{365}\right)$$

These transformed values were used as features for clustering. The number of clusters (K) was set to four, corresponding to the four seasons. The K-Means algorithm was run 100 times, and the best result (based on minimizing within-cluster variance) was selected. The resulting clusters, referred to as "heat wave families," represent distinct seasonal patterns of heat waves.

Spatial clustering was performed separately for each heat wave family using the UPGMA (Unweighted Pair Group Method with Arithmetic Mean) algorithm, a hierarchical clustering method. Spatial similarity between two heat waves, i and j, was quantified using the intersection strength (IS), defined as:

$$\text{IS}_{ij} = \frac{\text{IC}_{ij}}{\min(|L_{\text{set},i}|, |L_{\text{set},j}|)}$$

where $L_{\text{set},i}$ and $L_{\text{set},j}$ are the sets of grid cells covered by heat waves i and j, respectively, and IC_{ij} is the number of overlapping grid cells between the two heat waves.

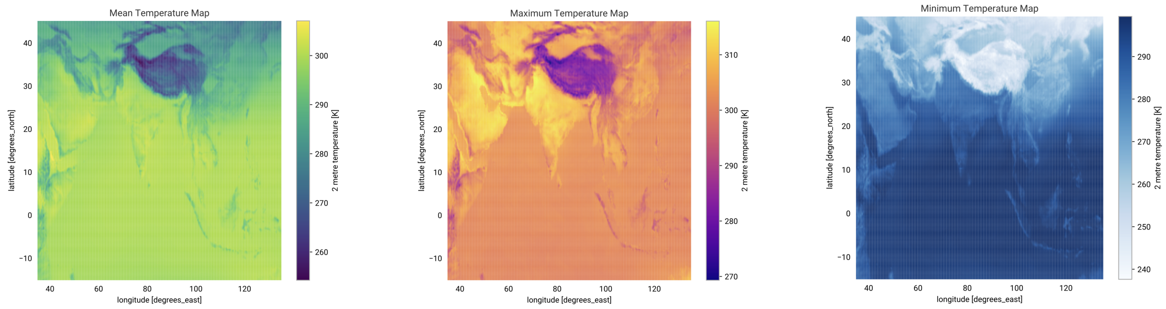
This two-step clustering approach enabled the identification of both temporal patterns (seasonal families) and spatial distributions of heat waves, providing a comprehensive understanding of their spatio-temporal dynamics.

4 Preliminary Data Analysis (PDA)

Before diving into the clustering and heatwave detection results, I conducted a preliminary analysis of the temperature data to understand its characteristics and trends. This section includes visualizations of average, mean, minimum, and maximum temperatures, as well as their temporal trends.

4.1 Mean, Maximum, and Minimum Temperatures

The mean, maximum, and minimum temperatures were analyzed to understand the overall temperature characteristics of the study region. Figure 2 shows these three plots combined into a single figure for better comparison.



(a) Mean Temperature (b) Maximum Temperature (c) Minimum Temperature

Figure 2: Mean, maximum, and minimum temperatures across the study region (1979–2018). Each plot represents the spatial distribution of the respective temperature metric.

4.2 Mean Temperature Trend

The mean temperature was calculated for each year to observe temporal variations. Figure 3 shows the trend of mean temperature over the years.

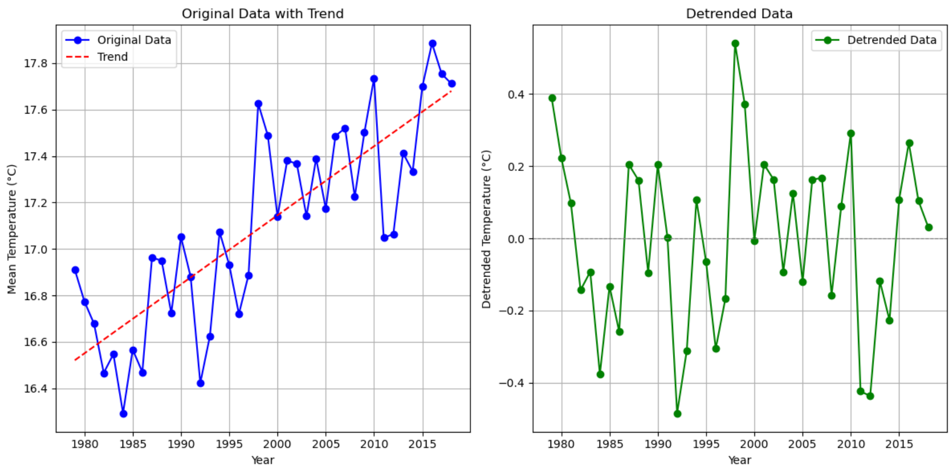


Figure 3: Trend of mean temperature over the years (1979–2018).

4.3 Seasonal Mean Temperature

To understand the seasonal mean temperature over the span of 40 years, Figure 4 shows the spatial distribution of seasonal mean temperatures.

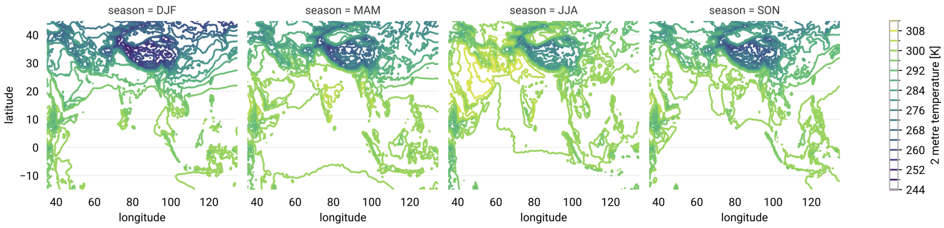


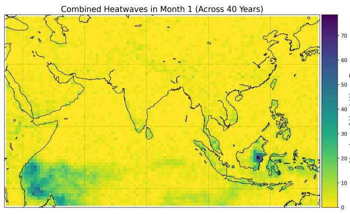
Figure 4: Spatial distribution of seasonal mean temperatures (1979–2018).

This preliminary analysis provides a foundation for understanding the temperature characteristics of the study region and highlights the need for further analysis of heatwave events.

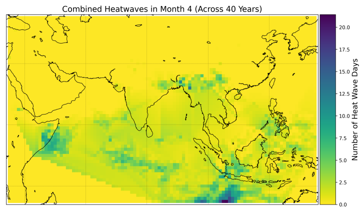
5 Results

5.1 Heat Wave Detection

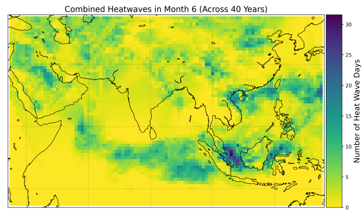
In this section, we present the detection of heat waves across different months and highlight the largest heat wave events based on their magnitude and spatial extent. The analysis includes visualizations of heat waves from four representative months (January, April, June, and November) and the largest heat waves detected during the study period.



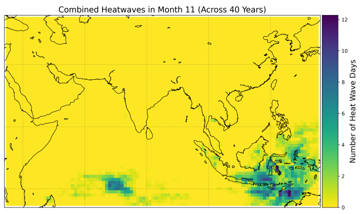
(a) January Heat Wave



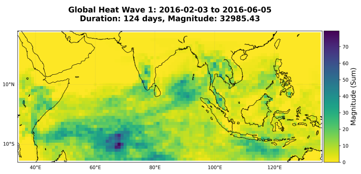
(b) April Heat Wave



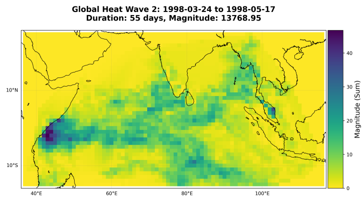
(c) June Heat Wave



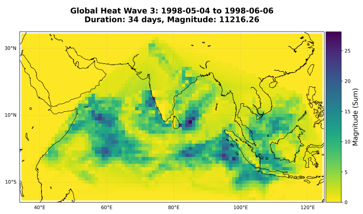
(d) November Heat Wave



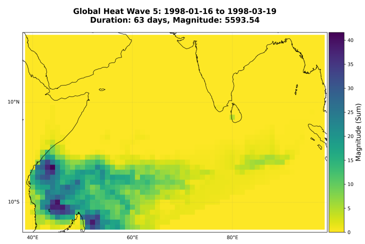
(e) Largest Heat Wave (1)



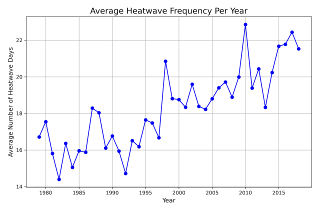
(f) Second Largest Heat Wave (2)



(g) Third Largest Heat Wave (3)



(h) Fifth Largest Heat Wave (5)



(i) Frequency of Heatwaves

Figure 5: Visualizations of heat waves detected across different months and the largest events. Each image illustrates the spatial extent and intensity of the heat wave during the specified period. Notably, the 2016 heat wave, as discussed in the World Weather Attribution report [3], and the 1998 heat wave, detailed in the IMD Pune publication [4], are clearly visible in these analyses. Additionally, the 2018 heat wave events are also evident, aligning with findings from these references.

5.2 Seasonal Families

The heat waves were clustered by their mean day of year using the K-means clustering algorithm, with $K = 4$. Using K=4 helps in finding seasonal heatwave patterns, resulting in different clusters based on heat-wave timing. The resulting clusters represent the four seasons, as shown in Figure 6. The four heat wave families are characterized as follows:

- **Family 0 (Winter)**: Spans from December to March and contains winter heat waves.
- **Family 1 (Summer)**: Spans from May to August and includes the most intense heat waves.
- **Family 2 (Fall)**: Spans from Mid-September to November and contains fall heat waves.
- **Family 3 (Spring)**: Spans from March to May and contains spring heat waves.

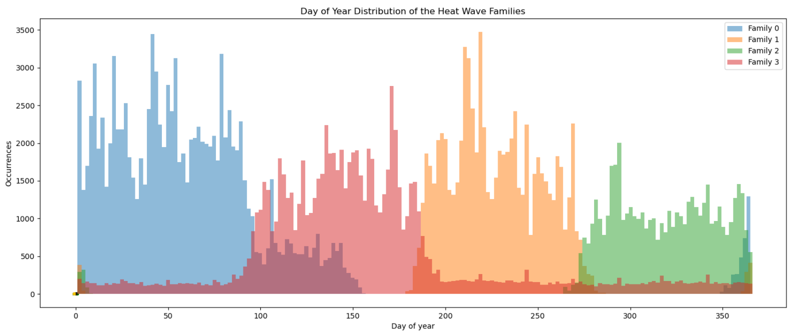
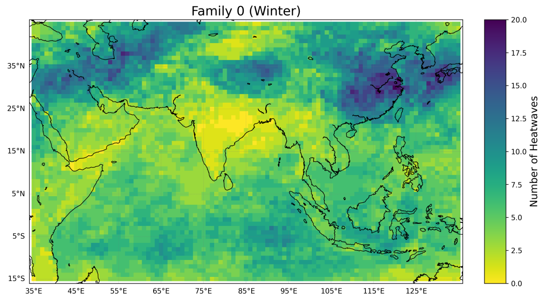
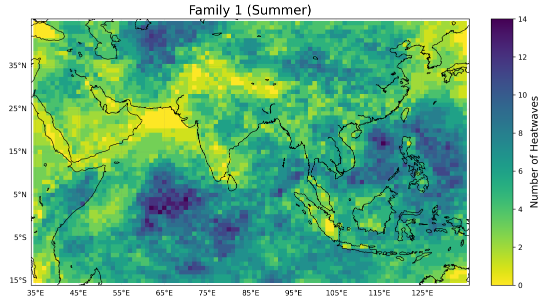


Figure 6: Day of year distribution of heat wave families. The histogram shows the distribution of heat wave days across the year. The four colors represent the four heat wave families identified using K-means clustering.

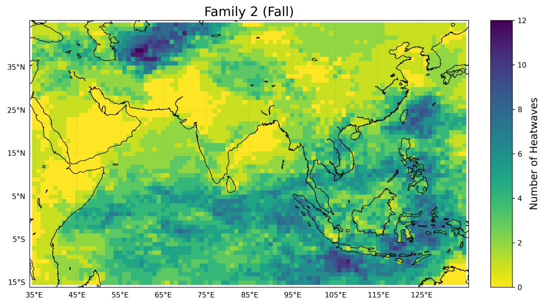
To further analyze the seasonal clustering, the spatial distribution of heat wave families is visualized in the following plots (Figures 7a to 7d). These plots highlight the geographic tendencies of heat waves for each season.



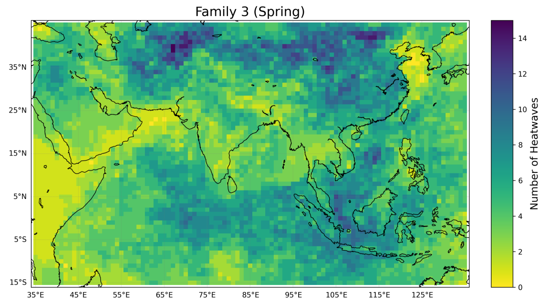
(a) Spatial distribution of Family 0 (Winter).



(b) Spatial distribution of Family 1 (Summer).



(c) Spatial distribution of Family 2 (Fall).



(d) Spatial distribution of Family 3 (Spring).

Figure 7: Spatial distribution of heat wave families. Each plot shows the geographic tendencies of heat waves for a specific season, as identified through K-means clustering.

5.3 Spatial Clusters

After K-means clustering, each heat wave family was clustered individually using UPGMA clustering to identify meaningful spatial heat wave clusters. The threshold for the number of UPGMA clusters per heat wave family was set to 3, given the low-resolution dataset. Dividing into 3 clusters provides information about the top 3 spatial hotspots for each family.

Figures 8 to 15 show the spatial distribution of the heat wave clusters for all families, along with their respective subfamilies. The colors indicate the number of heat waves occurring in a grid cell over the entire time span.

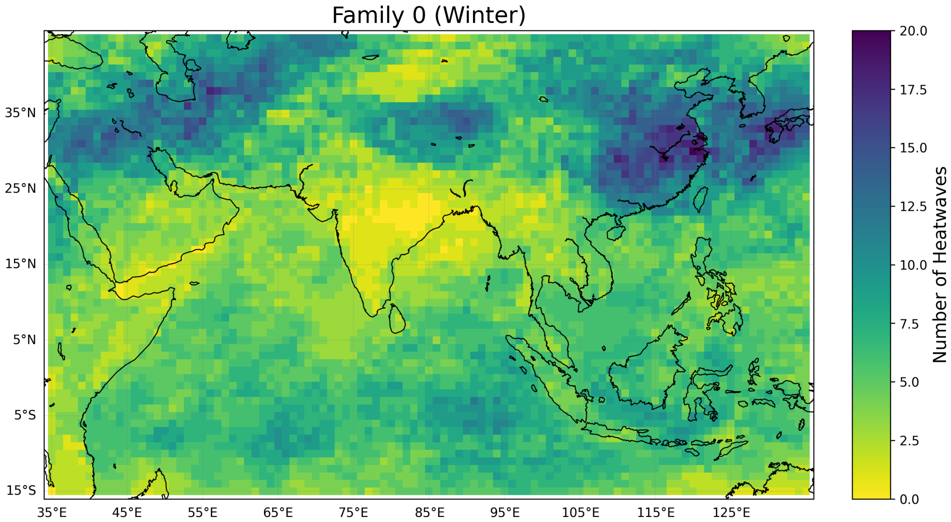
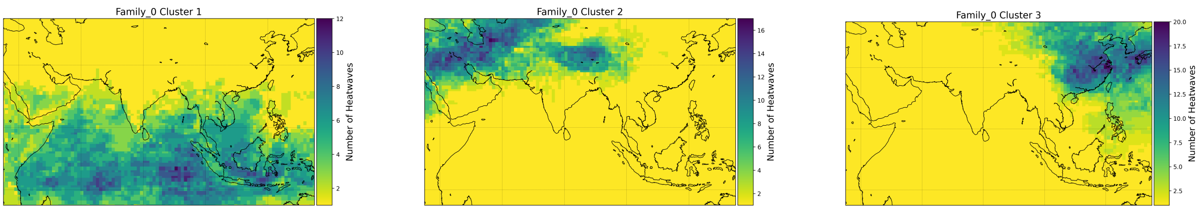


Figure 8: UPGMA clustering for Family 0 (Winter). The colors indicate the number of heat waves occurring in a grid cell over the entire time span.



(a) Subfamily 0.1 (Winter).

(b) Subfamily 0.2 (Winter).

(c) Subfamily 0.3 (Winter).

Figure 9: Subfamilies of Family 0 (Winter). Each subfamily represents a distinct spatial cluster of winter heat waves.

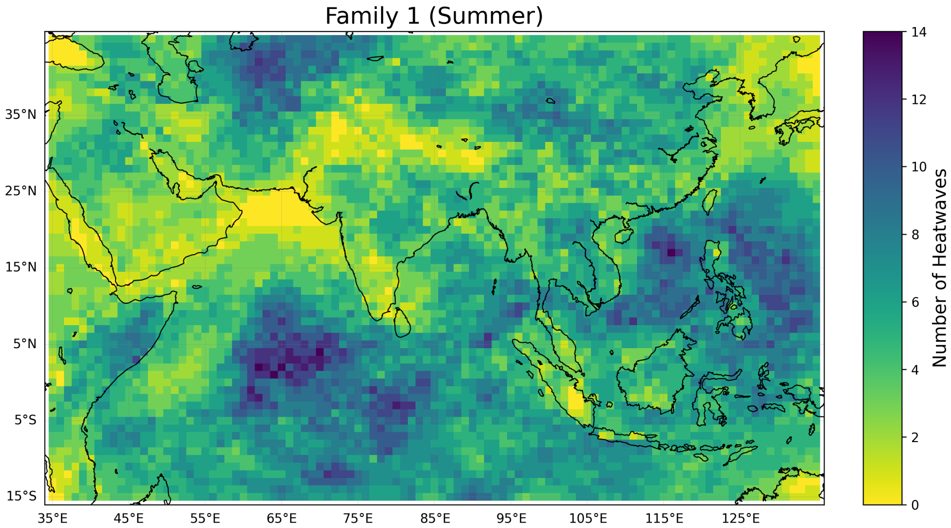
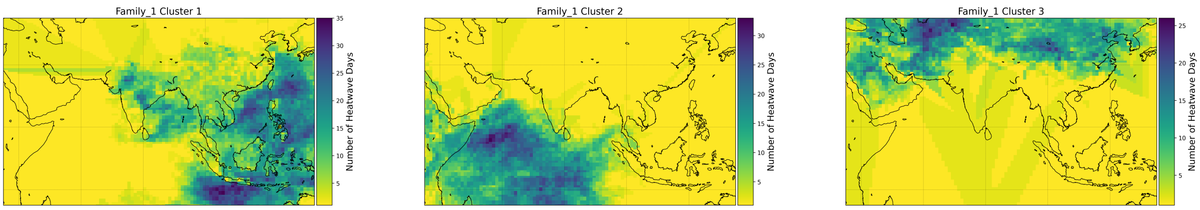


Figure 10: UPGMA clustering for Family 1 (Summer). The colors indicate the number of heat waves occurring in a grid cell over the entire time span.



(a) Subfamily 1.1 (Summer). (b) Subfamily 1.2 (Summer). (c) Subfamily 1.3 (Summer).

Figure 11: Subfamilies of Family 1 (Summer). Each subfamily represents a distinct spatial cluster of summer heat waves.

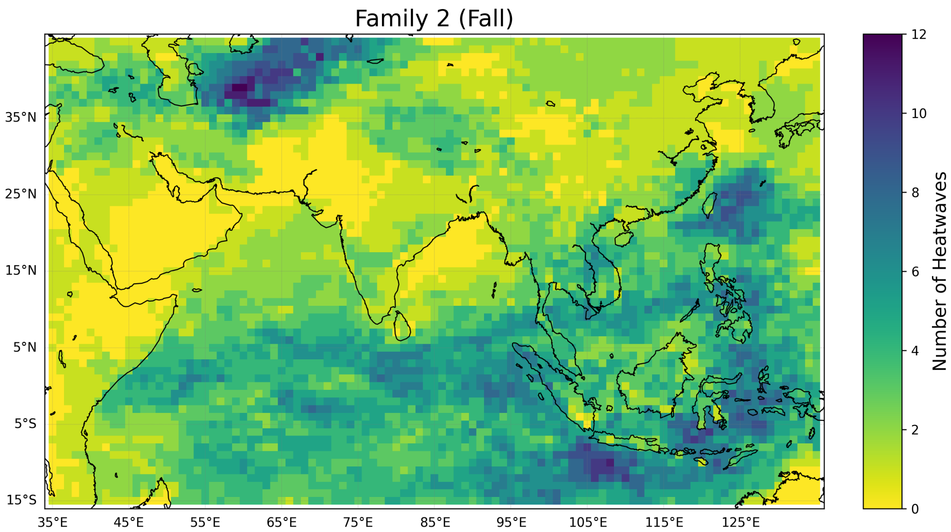
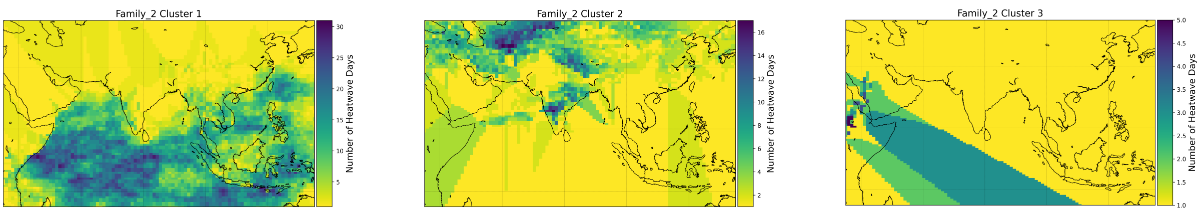


Figure 12: UPGMA clustering for Family 2 (Fall). The colors indicate the number of heat waves occurring in a grid cell over the entire time span.



(a) Subfamily 2.1 (Fall). (b) Subfamily 2.2 (Fall). (c) Subfamily 2.3 (Fall).

Figure 13: Subfamilies of Family 2 (Fall). Each subfamily represents a distinct spatial cluster of fall heat waves.

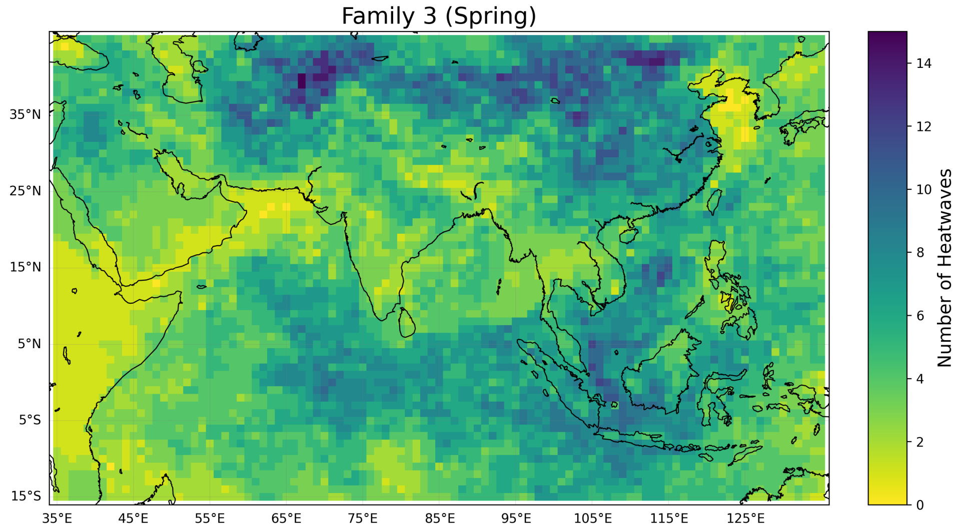
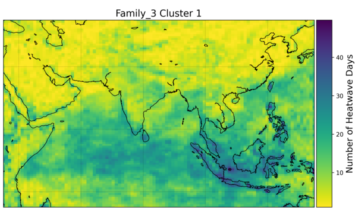
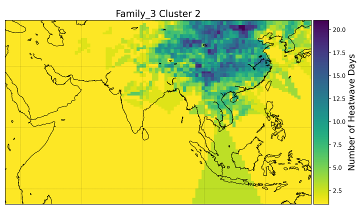


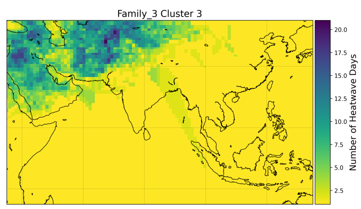
Figure 14: UPGMA clustering for Family 3 (Spring). The colors indicate the number of heat waves occurring in a grid cell over the entire time span.



(a) Subfamily 3.1 (Spring).



(b) Subfamily 3.2 (Spring).



(c) Subfamily 3.3 (Spring).

Figure 15: Subfamilies of Family 3 (Spring). Each subfamily represents a distinct spatial cluster of spring heat waves.

6 Discussion

6.1 Definition and Identification of Heat Waves

In this work, I developed a novel approach to define and identify heat waves as spatio-temporal phenomena, moving beyond grid-cell-based definitions and fixed regional boundaries. By using a quantile-based daily and grid-cell-dependent threshold, heat waves were detected across all climates and seasons. This method identified numerous heat waves in the study region between 1979 and 2018.

6.2 Spatio-Temporal Heat Wave Clusters Analysis

K-means clustering revealed the seasonal dependence of heat waves, dividing them into four families: winter, spring, summer, and fall. Attempts to incorporate additional features, such as HWMId magnitude or heat wave duration, did not improve clustering results, indicating that the mean day of year is the primary driver of variance in the data.

The distribution of heat wave durations is consistent across seasons, and the HWMId is often zero for non-summer heat waves, limiting its utility for clustering.

UPGMA clustering was used to identify spatial heat wave clusters within each family. The number of clusters was set to 3 due to the low resolution of the dataset. This revealed hotspots in regions like the Indian Ocean, Mainland China, Southeast Asia, India, Africa, and the Middle East.

Using U=3 significantly hindered the detailed study of clusters and heatwaves due to the low data resolution, providing limited insight. However, establishing this pipeline was crucial. Increasing the dataset's resolution in future work should yield more realistic results, identifying events and hotspots with greater accuracy.

This study provides a foundation for understanding the spatio-temporal dynamics of heat waves, but future work should focus on refining clustering methods, integrating additional variables, and assessing the ecological and climatic impacts of these events.

7 Conclusion and Outlook

- Established a modular pipeline for spatio-temporal clustering of heat waves. The pipeline is available on GitHub: Spatio-Temporal Heatwave Analysis.
- Identified four seasonal modes and regional hotspots over South and Southeast Asia.
- Future work: Increase dataset resolution, integrate NDVI and rainfall data, refine clustering methods, and develop early-warning tools. Adding variables like humidity, wind speed, etc., could also improve results.

The issue of extreme heat events is expected to become increasingly critical in the future, as even in a scenario with global warming limited to 1.5°C, the frequency and magnitude of heat waves are projected to rise. This underscores the importance of developing methods to predict heat waves in advance and to better understand their impacts across different scales.

The current definition of the HWMId does not fully align with the spatio-temporal heat wave definition proposed in this study. Adapting the HWMId to fit this new definition would allow for a more comprehensive assessment of heat wave intensity and magnitude, particularly for non-summer heat waves that are often underestimated.

Additionally, for clustering heat waves, it would be valuable to explore methods that integrate spatial and temporal clustering into a single unified approach. Such an approach could provide deeper insights into the dynamics of heat waves and help determine whether similar results to the current two-step clustering process can be achieved. These advancements would contribute significantly to improving our understanding of heat waves and their impacts in a changing climate.

8 References

References

[1] Traxl, D., et al. (2016a). Placeholder reference for Deep Graphs rainfall analysis. *Journal Placeholder*, Vol(Issue), Pages.

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Thank You

To my supervisor, friends, and family: thank you for believing in me and for inspiring me to push boundaries. This work is a reflection of your unwavering support and my dedication to making a meaningful contribution.

Here's to the pursuit of knowledge and the endless possibilities it brings. Thank you!

This project has been a journey of learning, exploration, and growth. I am deeply grateful to everyone who has supported me along the way—your encouragement and guidance have been invaluable.

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