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CHANGE POINTS DETECTION

APPLICATIONS IN VEGETATION AND TEMPERATURE ANALYSIS

RANIA NIRI

1. Introduction

Understanding climate change and its effects on vegetation and temperature dynamics has become a critical area of research due to its implications for ecosystems, biodiversity, and human activities. With increasing urbanization, land-use changes, and rising global temperatures, monitoring environmental transformations is essential for sustainable land management and climate adaptation. The ability to detect and quantify these changes over time is crucial for developing targeted interventions and ensuring the long-term sustainability of natural resources.

This report provides an in-depth analysis of temperature variations and key indices, including NDVI, NDBI, NDWI, and NDGlaI, across selected communes in Geneva, Evian, and Fribourg. These indices serve as essential indicators for understanding land surface changes, urbanization impacts, and hydrological variations. However, due to data limitations, the primary focus of this study will be on NDVI and temperature, as they provide the most comprehensive and reliable insights into vegetation health and climate variability. While NDGlaI and NDBI offer valuable information, their dataset coverage is limited, particularly in winter months, making their use less robust for long-term analysis.

By examining seasonal shifts in vegetation and land surface temperature trends, this study aims to assess correlations between temperature dynamics and vegetation health over time, offering insights into potential climate adaptation strategies. To achieve this, the study incorporates advanced methodologies such as change point detection with Ruptures and Hidden Markov Models (HMM) to extract meaningful insights from remote sensing data.

The selection of communes for this study was guided by the framework established by the TRACES project, a collaborative research initiative between France and Switzerland. The project focuses on three primary study areas:

1. **Fribourg Study Area**: Comprising 127 Swiss municipalities, including and surrounding Fribourg.
2. **Grand Genève Study Area**: Encompassing 209 municipalities across Switzerland and France, centered around Geneva.
3. **Évian Study Area**: Consisting of 45 French municipalities in and around Évian.

These areas collectively cover more than 317 municipalities, reflecting a wide geographical and environmental diversity. The selection criteria were based on the availability of comprehensive environmental data from the Swiss Data Cube (SDC) [1], which offers extensive satellite imagery and environmental indices for these regions. This data availability ensures a robust foundation for analyzing environmental trajectories and changes over time.

Geneva, Evian, and Fribourg were chosen as study areas due to their diverse environmental and climatic characteristics. Geneva, as a highly urbanized region, provides insights into anthropogenic impacts on land surface temperature and vegetation patterns. Its dense infrastructure and rapid development necessitate a thorough examination of urban heat island effects and green space dynamics. Evian, with its proximity to natural landscapes and water bodies, serves as a model for analyzing water-vegetation interactions, making it particularly relevant for assessing climate-induced hydrological changes. Fribourg, characterized by its mountainous terrain and significant elevation gradients, offers a unique perspective on altitude-related vegetation dynamics and climate variability. By integrating these three diverse geographical settings, the study presents a comprehensive framework for understanding the interplay between environmental factors, climate change, and urbanization.

Additionally, observations from the Land Information System (LIS) and Land Surface Temperature (LST) datasets were utilized, covering the period 1985 to 2022. These observations were available at monthly, daily, yearly, and seasonal scales, providing a comprehensive temporal analysis of environmental variations across the selected regions.

By focusing on these specific communes, the study leverages the rich dataset provided by the SDC, facilitating detailed and accurate assessments of environmental changes and supporting the overarching goals of the TRACES project [2].

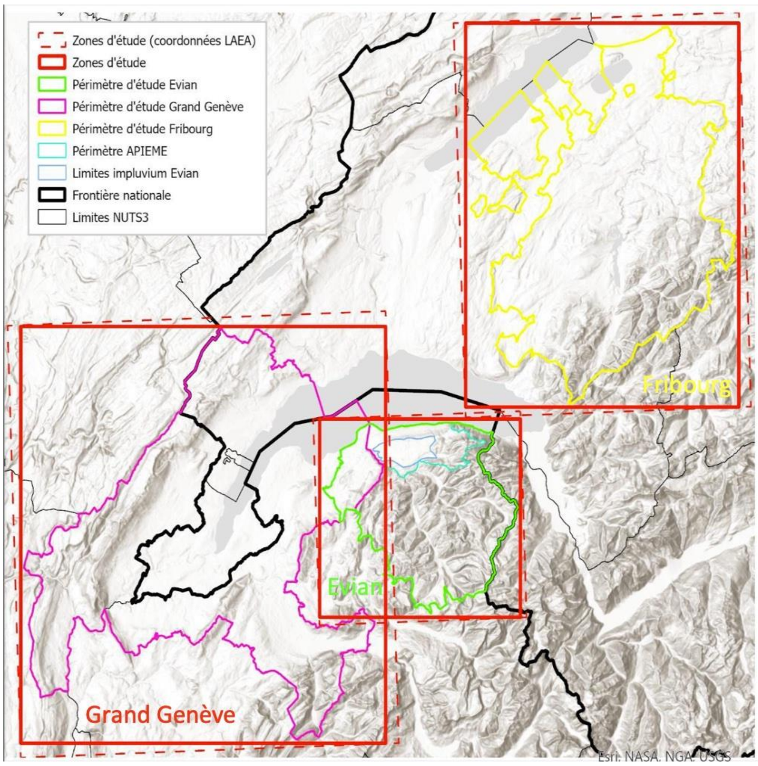


Figure 1: The 3 TRACES Project Study Areas

This map provides a visual representation of the study regions, including national borders, watershed limits, and regional perimeters, aiding in the spatial understanding of dataset coverage and facilitating comparative spatial analysis.

2. Objectives

The primary objective of this study is to analyze and quantify environmental changes using remote sensing data, specifically focusing on temperature variations and vegetation dynamics. This is achieved through both inter-annual and intra-annual analyses, each targeting different temporal scales and environmental processes.

Inter-annual Analysis

- The goal is to study long-term seasonal shifts and changes in seasonal duration by analyzing key variables like NDVI and temperature across multiple years.
- This analysis will help identify long-term trends, such as earlier or delayed seasonal peaks, and possible changes in the duration of vegetation growth and heat cycles, which are critical for understanding broader climatic impacts on ecosystems.
- By detecting gradual shifts over extended periods, this approach provides valuable insights into the cumulative effects of climate change on vegetation patterns and thermal regimes.

Intra-annual Analysis

- The objective is to detect abrupt change points within individual years, focusing on identifying events or anomalies that significantly alter the trend of NDVI or temperature.
- Such change points could correspond to extreme climatic events, anthropogenic disturbances, or natural phenomena such as droughts, heatwaves, and rapid urban expansion.
- By identifying short-term deviations from expected seasonal trends, this analysis aids in early-warning system development and rapid response strategies for mitigating environmental degradation.

The combination of these two analytical perspectives ensures a robust and comprehensive understanding of environmental dynamics, capturing both gradual and sudden changes in the regions studied.

3. State of the Art

In recent years, advancements in remote sensing technologies and analytical methods have significantly improved our ability to monitor environmental changes. Remote sensing, particularly through satellite imagery, remains a central tool for environmental monitoring, providing high-resolution, large-scale, and frequent observations of Earth's surface. Vegetation indices like NDVI commonly used to track vegetation health and productivity, offering critical insights into how temperature, precipitation, and other climatic factors influence vegetation growth. While NDVI is effective for capturing broad patterns of vegetation dynamics, its sensitivity can be limited in certain contexts, such as areas with complex land use or during seasonal transitions.

To address these challenges, a recent python library called Ruptures [3] has emerged as an important tool for detecting changes in time-series data by breaking it into seasonal, trend, and residual components. This method allows for the identification of both abrupt shifts and gradual trends [4], making it particularly useful for monitoring vegetation and temperature over long periods. Ruptures has been widely applied in remote sensing analysis, especially in studies examining land cover and vegetation dynamics where seasonal variations are significant.

Similarly, BFAST (Breaks For Additive Season and Trend) [5] has emerged as an important tool for detecting changes in time-series data by breaking it into seasonal, trend, and residual components. This method allows for the identification of both abrupt shifts and gradual trends, making it particularly useful for monitoring vegetation and temperature over long periods. BFAST has been widely applied in remote sensing analysis, especially in studies examining land cover and vegetation dynamics where seasonal variations are significant [6]. By accounting for seasonality and trend, BFAST provides a nuanced understanding of environmental change, especially in regions subject to both natural climate variations and anthropogenic disturbances.

Another important method in this domain is BEAST (Bayesian Estimation of Abrupt Shifts in Trends), which leverages Bayesian statistical techniques to detect abrupt changes in environmental data, particularly in time series where trends may evolve in response to climate change. BEAST has been used in various studies to assess temperature shifts and vegetation productivity changes, providing a probabilistic framework that accounts for uncertainty in environmental data [7]. This method is particularly useful when working with incomplete or noisy data, which is common in remote sensing datasets where cloud cover, sensor errors, or missing data points can complicate analyses. BEAST's ability to model uncertainty allows researchers to better understand the timing and likelihood of environmental changes, making it a valuable tool for climate impact studies.

The integration of Hidden Markov Models (HMMs) [8] has further enhanced our understanding of environmental dynamics [9]. HMMs are ideal for modeling temporal data that evolve through a series of hidden states, with transitions between these states occurring probabilistically. This method has been applied to analyze shifts in vegetation and temperature patterns, where gradual transitions are not easily captured by traditional change point detection methods. By capturing both abrupt and gradual transitions in environmental processes, HMMs provide a flexible framework for understanding complex environmental dynamics, particularly in relation to climate variability.

In addition to statistical methods, machine learning models such as random forests [10] and support vector machines (SVMs) [11] have been increasingly used to classify and predict environmental changes based on remote sensing data. These models are effective at handling large, high-dimensional datasets, such as those generated by satellite imagery, and can detect complex patterns in climate and vegetation data that may not be apparent through traditional methods. Deep learning models, particularly long short-term memory (LSTM) networks [12], have also gained traction in analyzing time-series data for environmental monitoring. LSTMs excel at capturing long-term dependencies in data, making them well-suited for studying the dynamics of vegetation and temperature over extended periods [13].

Despite these advancements, challenges remain in handling missing or incomplete data, particularly during periods when cloud cover obscures satellite imagery or when seasonal gaps limit the availability of reliable data. To address this, new techniques such as data imputation methods, including machine learning algorithms like k-nearest neighbors (KNN) and deep learning approaches, are being explored to predict missing values and improve the continuity of time-series datasets [14] [15].

4. Methodology

4.1 Data Sources

To achieve a thorough and accurate assessment, the following key data sources were used:

- **Temperature Data**: Extracted from high-resolution remote sensing sources, providing insights into land surface temperature variations across different time scales.
- **NDVI (Normalized Difference Vegetation Index)**: Used to analyze vegetation health, productivity, and seasonal growth patterns. NDVI serves as a crucial indicator for detecting vegetation stress and phenological shifts.
- **NDBI (Normalized Difference Built-up Index)**: Assessed urban expansion and land-use changes, helping to quantify the extent of anthropogenic influence on land cover. NDBI was not included in the primary analysis due to its limited application for the specific seasonal dynamics studied in this research.
- **NDWI (Normalized Difference Water Index)**: Evaluated water bodies and moisture content, particularly useful for understanding hydrological cycles and their impact on vegetation. This will be included in future studies.
- **NDGlaI (Normalized Difference Glacier Index)**: Analyzed glacier coverage in high-altitude regions. However, this index was excluded from seasonal analysis due to the lack of winter data, making it less reliable for comprehensive climate assessments.

4.2 Change Point Detection Methods

To analyze temporal changes in vegetation and temperature trends, we employ two key methodologies:

4.2.1 Ruptures Algorithm

Ruptures is a Python-based library designed for detecting change points in time series data. It identifies significant shifts in statistical properties such as mean, variance, or trend, using various segmentation algorithms. This method is widely used in environmental studies due to its efficiency and flexibility in handling complex time-series data.

The Ruptures library offers various segmentation algorithms, each with different strengths and computational trade-offs:

4.2.1.1 PELT (Pruned Exact Linear Time Algorithm)

- **Overview**: The PELT algorithm is designed to identify the most optimal segmentation of time series data by minimizing a penalized cost function. The method is particularly effective in providing an accurate segmentation while ensuring efficient computational performance.
- **How It Works**: PELT is based on dynamic programming but incorporates a pruning strategy to improve performance. It evaluates different potential segmentation points and prunes those that are unlikely to lead to an optimal segmentation, which significantly reduces the number of computations.
- **Key Strengths**:
    - **Optimal Segmentation**: PELT aims to find the most likely change points that minimize the cost function, ensuring the segmentation is as accurate as possible.
    - **Computational Efficiency**: The pruning strategy helps ensure that the algorithm works in **linear time**, making it suitable for large datasets.
    - **Application**: Particularly useful for detecting multiple change points over long time periods, such as identifying gradual shifts in vegetation or temperature over years.

4.2.1.2 Binary Segmentation (Binseg)

- **Overview**: Binary Segmentation is a simpler, recursive, top-down approach that detects change points in a sequential manner. This method is less computationally intensive but sacrifices some level of optimality in exchange for speed.
- **How It Works**: The algorithm works by splitting the time series into two parts at each iteration and testing whether there is a significant change between these two segments. If a change point is detected, the algorithm continues to split the time series recursively. It repeats this process until no further changes are detected or a predefined stopping criterion is met.
- **Key Strengths**:
    - **Quick Detection**: Binseg is fast and suitable for approximate segmentation, which can be beneficial when real-time or large-scale processing is required.
    - **Less Computational Cost**: The simplicity of the method ensures low computational overhead, making it suitable for quick explorations of time series data.
    - **Flexibility in Number of Change Points** : The algorithm allows you to specify the number of change points you want to detect, making it particularly useful for controlling the granularity of segmentation and focusing on major shifts within the data.
    - **Application**: Ideal for cases where the exact segmentation is less important, but an approximate segmentation of large datasets is needed quickly (e.g., preliminary analysis of seasonal trends).

4.2.1.3 Dynamic Programming (Dynp)

- **Overview**: The Dynamic Programming algorithm seeks to find the globally optimal segmentation of the time series, considering all potential change points. This method is the most computationally expensive but is considered the gold standard for accurate change point detection.
- **How It Works**: **Dynp** works by exhaustively searching through all possible ways to divide the time series into segments. It evaluates all potential change points and then selects the one that minimizes the cost function, ensuring that the segmentation is optimal over the entire time series.
- **Key Strengths**:
  - **Optimal Segmentation**: **Dynp** guarantees that the detected change points represent the true underlying shifts in the data, making it ideal for highly accurate analysis.
  - **High Precision**: Because the method evaluates all possible segmentations, it provides the most reliable and precise results, particularly when the data is complex and non-linear.
  - **Application**: Best suited for smaller datasets or cases where computational resources are available, and the highest level of segmentation accuracy is required (e.g., detecting abrupt climate shifts in highly sensitive regions).

4.2.1.4 Cost Functions

The performance of the algorithms in Ruptures depends on the cost function used to evaluate the fit of the segmented time series. The cost function determines how well the data fits into the segmented parts and influences the algorithm's sensitivity in detecting change points. Two common cost functions used are:

- **L2 Cost Function (Mean-Based Segmentation)**: This cost function minimizes the squared difference between the data points and the mean of each detected segment. The goal is to find segments where the change in the mean is as significant as possible.

  $$Cost = \sum_{i \in S} (x_i - \mu_s)^2$$

  where S represents a detected segment, x_i are data points, and μ_s is the mean of the segment. This cost function is commonly used when the change in the mean of the data is of primary interest.

- **Radial Basis Function (RBF) Cost**: This cost function accounts for changes in variance within the segments. It is useful for situations where detecting shifts in variance is as important as detecting shifts in the mean, such as identifying structural changes or sudden fluctuations in the data.

$$Cost = \sum_{i \in S} (\exp\left(-\frac{(x_i - \mu_s)^2}{\sigma^2}\right))$$

where σ is a penalty term that adjusts for changes in variance. This function is helpful in situations where shifts in data variability are the focus of the analysis.

- **Normal Cost Function (Squared Error) :** also known as the sum of squared errors, is a standard cost function used in regression problems and time series analysis. It measures the discrepancy between the observed data points and the predicted values. In the context of change point detection, it helps to identify the points where the predicted values based on the previous segments no longer align with the actual data, signaling a change point.

$$Cost = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Where y_i are the observed values, $\hat{y}_i$ are the predicted values and n is the number of data points.

4.2.2 Hidden Markov Models (HMM)

Hidden Markov Models (HMM) are a powerful statistical tool used to model time-series data, particularly when the data evolves through different underlying states that are not directly observable. These "hidden" states represent distinct environmental conditions or phases, and the system transitions between these states over time. For example, in environmental studies, the hidden states might represent different trends in data such as:

- **Stable Trend**: No significant changes in the environmental variable (e.g., temperature, vegetation health).
- **Increasing Trend**: A period of gradual increase in the environmental variable (e.g., warming temperatures, growing vegetation).
- **Decreasing Trend**: A period of gradual decline in the environmental variable (e.g., cooling temperatures, deteriorating vegetation).

The key feature of HMM is that the transitions between these hidden states are probabilistic rather than deterministic. In other words, the system has a certain probability of transitioning from one state to another at each time step, and this probability can vary depending on the current state and time series data. In the context of environmental change detection:

- **Hidden States**: The model assumes that the system is in one of several hidden states at any given point in time, but these states are not directly observed. The observable data (e.g., temperature, vegetation indices) are influenced by the underlying hidden state.
- **State Transitions**: The transitions between these hidden states are governed by transition probabilities. These probabilities define the likelihood of moving from

one state to another, which can capture the progression or abruptness of environmental changes.

- **Emission Probabilities**: At each time point, the model observes the environmental data (such as temperature or NDVI), which is assumed to be emitted based on the hidden state. The emission probabilities model the relationship between the hidden states and the observed data.
- **Learning from Data**: HMM can be trained on historical data to estimate the transition and emission probabilities. This enables the model to "learn" how environmental variables evolve and detect both abrupt (e.g., sudden temperature spikes) and progressive changes (e.g., gradual shifts in vegetation health).

This figure below illustrates the results of applying the Hidden Markov Model (HMM) to NDVI data for the commune CH6630. The blue line represents the high vegetation periods, where NDVI values are elevated, indicating healthy and active vegetation. The orange line corresponds to low vegetation periods, where NDVI values drop, indicating reduced vegetation activity or stress. The purple dashed line marks the boundary NDVI threshold, which separates the high vegetation state from the dormancy state. This segmentation allows for a clear identification of periods when vegetation is thriving versus when it is low, providing insights into the seasonal dynamics of vegetation health.

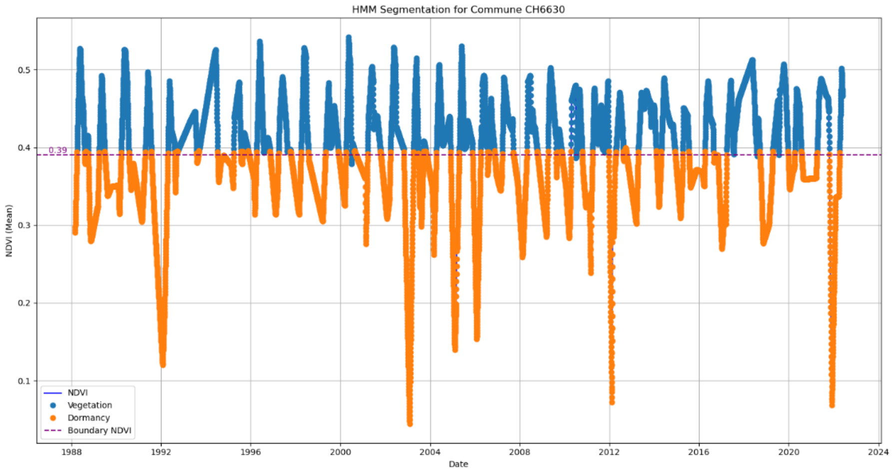


Figure 2: An Example of HMM Segmentation for NDVI

The benefits of using HMM for environmental change detection include:

- **Modeling Complex Patterns**: HMM is especially effective when the time series has underlying patterns that change over time, such as environmental systems that can shift between different conditions (e.g., stable, increasing, or decreasing trends).
- **Improved Detection of Environmental Changes**: By modeling transitions between hidden states, HMM can improve the detection of both abrupt changes (e.g., a sudden shift in temperature) and progressive changes (e.g., a slow trend in vegetation decline).

- **Probabilistic Approach**: The probabilistic nature of HMM allows it to account for uncertainty in the transitions between states, which is especially useful in noisy or incomplete data where exact state changes are difficult to detect.
- **Flexibility**: HMM can be adapted to model a variety of environmental phenomena by defining appropriate hidden states that reflect different conditions in the system.

Hidden Markov Models are a valuable tool for environmental studies, particularly for understanding how systems evolve over time by detecting the underlying states (e.g., stable, increasing, decreasing). The probabilistic nature of HMM makes it a powerful approach for capturing both gradual and sudden environmental changes, improving the accuracy and reliability of change detection in time-series data.

By integrating Ruptures for abrupt change detection and **HMM** for modeling gradual transitions, this study ensures a comprehensive approach to understanding vegetation and temperature dynamics over time.

5. Results and Discussion

5.1 Trends in NDVI and Temperature

The analysis of long-term trends in NDVI and temperature provides insight into the evolving environmental conditions in Geneva, Evian, and Fribourg. These two variables were chosen due to their strong and consistent trends, high correlation, and direct relevance to climate and ecological dynamics. The following Figure presents an example of the long-term trends in NDVI and temperature for Geneva, where the data clearly illustrates how these variables evolve over time.

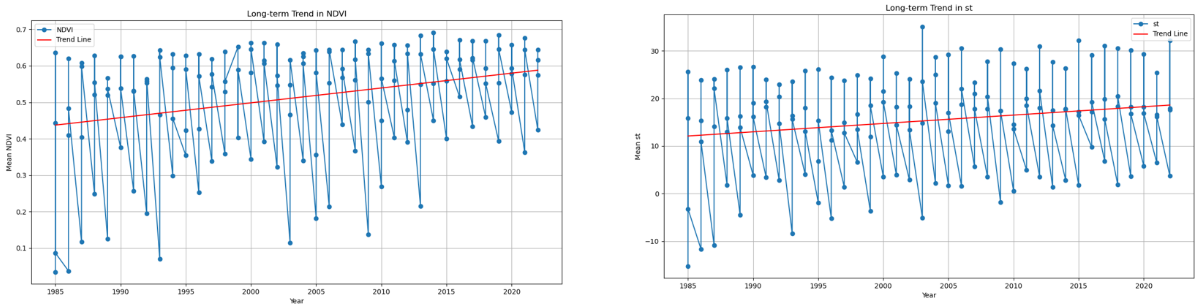


Figure 3: Trend in NDVI and Temperature for Geneva

In the left plot of *Figure 3*, the NDVI data for Geneva indicates a gradual upward trend over time, suggesting an overall increase in vegetation cover. The consistent seasonal fluctuations highlight regular phenological cycles, with vegetation peaks in warmer months and dormancy in colder months. This long-term increase in NDVI may be attributed to factors such as climate-induced shifts favoring plant growth, reforestation efforts, or improved land management practices.

The observed correlation between NDVI and temperature supports the idea that rising temperatures may be contributing to extended growing seasons and increased vegetation productivity. However, the influence of urbanization and land-use changes should also be considered in future studies, as these factors may modulate or enhance the effects of climate change on vegetation health.

In the right plot, the temperature trend suggests a gradual increase over time, consistent with global warming patterns. The seasonal fluctuations are substantial, with higher temperatures in summer and lower in winter, reinforcing the need for seasonal-trend analysis to differentiate long-term warming effects from natural variability. This long-term temperature increase is indicative of broader climate changes, potentially affecting both vegetation cycles and local weather patterns.

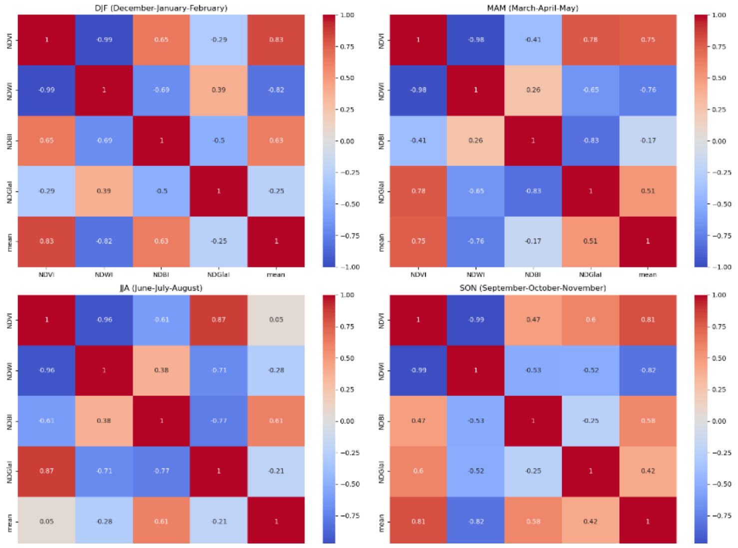
Rising temperatures can directly impact vegetation cycles, altering the timing of plant growth, flowering, and dormancy. Additionally, temperature variations influence water availability, soil moisture, and evaporation rates, further affecting ecosystem health and sustainability.

5.2 Correlation Study

A correlation analysis was performed to evaluate the relationship between NDVI and temperature across different seasons (DJF, MAM, JJA, SON). The correlation coefficients for each season are visualized in the heatmap below. Key findings include:

- **NDVI & Temperature**: A strong positive correlation was observed across all seasons, indicating that warmer temperatures are generally associated with increased vegetation activity. This suggests that higher temperatures contribute to more significant vegetation growth, particularly during warmer months.
- **NDVI & Water Availability**: In certain seasons, negative correlations between NDVI and water-related indices (e.g., NDWI) were found. This indicates that higher vegetation cover may coincide with reduced surface water levels, possibly due to increased evapotranspiration, particularly during the warmer months.
- **Temperature & Seasonal Variability**: Temperature fluctuations significantly influence NDVI dynamics. These fluctuations are crucial in determining seasonal vegetation growth, reinforcing the role of temperature as a primary climate variable impacting vegetation cycles.

The following heatmap (*Figure 4*) shows the correlation coefficients between NDVI, NDWI, NDBI, and NDGlaI across four seasons: DJF (December-January-February), MAM (March-April-May), JJA (June-July-August), and SON (September-October-November). The color scale represents the strength of the correlation, with red indicating a positive correlation and blue indicating a negative correlation. The diagonal values represent the correlation of each variable with itself, which is always 1.



DJF (December-January-February)

	NDVI	NDWI	NDBI	NDGlal	mean
NDVI	1	-0.99	0.65	-0.29	0.83
NDWI	-0.99	1	-0.69	0.39	-0.82
NDBI	0.65	-0.69	1	-0.5	0.63
NDGlal	-0.29	0.39	-0.5	1	-0.25
mean	0.83	-0.82	0.63	-0.25	1

MAM (March-April-May)

	NDVI	NDWI	NDBI	NDGlal	mean
NDVI	1	-0.98	-0.41	0.78	0.75
NDWI	-0.98	1	0.26	-0.65	-0.76
NDBI	-0.41	0.26	1	-0.83	-0.17
NDGlal	0.78	-0.65	-0.83	1	0.51
mean	0.75	-0.76	-0.17	0.51	1

JJA (June-July-August)

	NDVI	NDWI	NDBI	NDGlal	mean
NDVI	1	-0.96	-0.61	0.87	0.05
NDWI	-0.96	1	0.38	-0.71	-0.28
NDBI	-0.61	0.38	1	-0.77	0.61
NDGlal	0.87	-0.71	-0.77	1	-0.21
mean	0.05	-0.28	0.61	-0.21	1

SON (September-October-November)

	NDVI	NDWI	NDBI	NDGlal	mean
NDVI	1	-0.99	0.47	0.6	0.81
NDWI	-0.99	1	-0.53	-0.52	-0.82
NDBI	0.47	-0.53	1	-0.25	0.58
NDGlal	0.6	-0.52	-0.25	1	0.42
mean	0.81	-0.82	0.58	0.42	1

Figure 4: Seasonal Correlation Heatmaps

The results confirm that temperature rise significantly influences NDVI trends, supporting the hypothesis that climate-induced changes affect vegetation cycles. The seasonal variations indicate that vegetation's response to temperature changes is not uniform. It may be influenced by other factors such as precipitation, soil conditions, and human activities. These correlations underscore the importance of considering multi-variable interactions when studying climate effects on vegetation.

5.3 Change Points Detection

5.3.1 Data Selection and Filtering

To ensure data quality and consistency, the study employed a rigorous filtering process before conducting any analyses. The dataset consisted of daily NDVI and temperature observations, which were aggregated at a monthly level for further processing. The key filtering criteria included:

- **Temporal Constraints:** Only data from 1987 onwards were included to ensure good data accuracy for trend analysis.
- **Quality Threshold:** Data points with a quality score (qual) below 0.8 were excluded to minimize errors and ensure reliable observations**.**
- **Adjusted Threshold for Post-2003 Data:** Due to the Landsat 7 Scan Line Corrector (SLC) failure in 2003, a revised threshold of 0.59 was applied to the data after 2003. This adjustment was made to ensure consistent data retention before and after the failure. Before 2003, a threshold of 0.8 was used to ensure high-quality data. The adjusted thresholds for each region were 0.57 for Grand Genève, 0.59 for Evian, and 0.60 for Fribourg. These thresholds maintained consistency across regions, accommodating the effects of the SLC failure.
- **Aggregation Method:** Since the raw dataset consisted of daily observations, it was aggregated into 12 monthly values per year, ensuring a balance between temporal resolution and computational feasibility.

These filters were applied to maintain the integrity of the dataset and enhance the reliability of subsequent analyses, including the change point detection process.

5.3.2 Inter-annual Approach

To analyze the inter-annual variations in NDVI and temperature, we implemented a change point detection approach. The goal was to identify two significant transition points per year:

- **Vegetation Period Detection:**
    - The start of the high vegetation season, marking the onset of plant growth.
    - The end of the high vegetation season, indicating the transition to dormancy.
- **Temperature Season Detection:**
    - The beginning of the heat season, corresponding to rising temperatures.
    - The end of the heat season, marking a return to cooler conditions.

This segmentation allows us to assess shifts in vegetation and temperature cycles over time, providing insights into how climate variability influences ecosystem dynamics.

5.3.2.1 Change Point Detection with Ruptures

To detect change points in NDVI and temperature time-series data, we applied the Ruptures Python library, which offers various segmentation algorithms for offline change detection.

Methodology

We implemented the Binary Segmentation (Binseg) algorithm, which recursively partitions the data into segments by detecting abrupt shifts in statistical properties.

- **Input:** NDVI and temperature time series.
- **Cost Function:** Mean-based segmentation (L2 norm).
- **Number of Breakpoints:** Fixed at two per year, capturing the start and end of vegetation and temperature seasons.

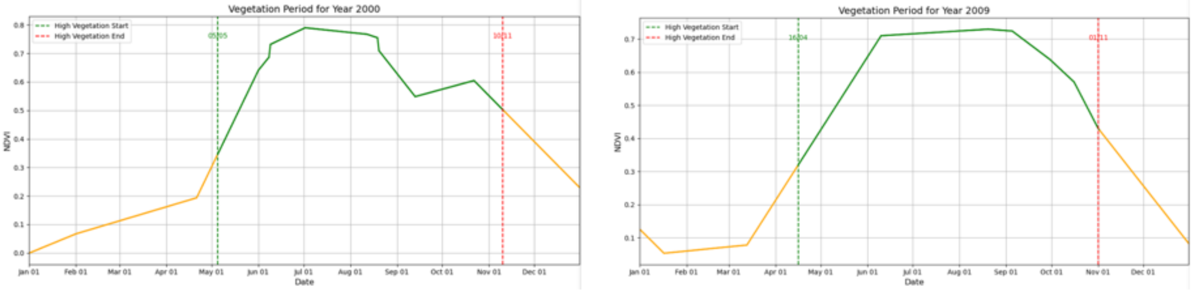


Figure 5: Vegetation Period Detection for Year 2000 and Year 2009 (Evian - FR74063)

Figure 5 shows the detected vegetation period for the years 2000 (left) and 2009 (right) for Evian (FR74063). The green dashed lines indicate the start of the high vegetation season, marking the onset of plant growth. The red dashed lines mark the end of the high vegetation season, signifying the transition to dormancy. The plots illustrate how the high vegetation season fluctuates across different years, providing insights into the timing and duration of vegetation growth.

Limitations of Ruptures

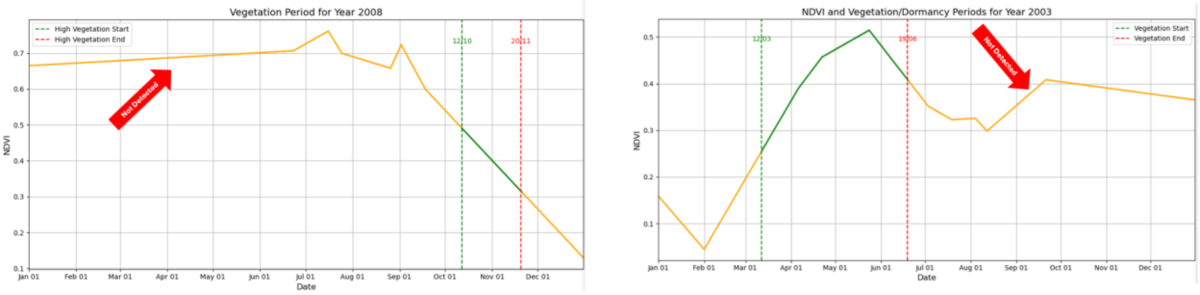


Figure 6: Failure in Vegetation Period Detection using Ruptures

Figure 6 highlights some limitations of the Ruptures algorithm in detecting the vegetation periods for specific years, such as 2008 and 2003. In these plots:

- The 2008 plot (left) shows a situation where the start of the high vegetation period was not detected correctly in the early months of the year (indicated by the red arrow). The algorithm fails to identify the actual onset of the vegetation period in this case.
- The 2003 plot (right) also shows an instance where the end of the vegetation period was not detected correctly (indicated by the red arrow). The algorithm struggles to detect the transition to dormancy, which might be caused by unusual climatic or data quality issues in that year

While the Ruptures algorithm is effective in detecting change points, certain limitations can affect its accuracy, particularly in cases where the transitions are subtle or where data quality is compromised:

- **Detection Gaps**: In some years, the Ruptures algorithm failed to detect the start or end of the vegetation periods. For example, in 2008, the start of the vegetation period was not detected accurately, as shown in the left plot of Figure 6, where the red arrow indicates the missed detection.
- **Sensitivity to Anomalies**: The Ruptures algorithm can struggle to handle years with unusual transitions, such as 2003, as shown in the right plot of Figure 6. The failure to detect the end of the vegetation period (marked by the red arrow) is likely due to irregular seasonal changes or data quality issues during that year.
- **Impact of Data Quality**: The algorithm is sensitive to the quality and resolution of input data. Missing data or low-resolution time series can lead to inaccurate change point detection, especially in regions where seasonal cycles are irregular or affected by sensor anomalies.

5.3.2.2 Change Point Detection with Hidden Markov Models (HMMs)

To improve the robustness of seasonal transition detection, we applied Hidden Markov Models (HMMs), which probabilistically model temporal dependencies between states. The HMM approach offers a more sophisticated method for detecting changes in vegetation and temperature cycles by allowing for gradual transitions, rather than the abrupt shifts modeled by Ruptures.

Methodology

The same data and filtering criteria used for Ruptures were applied to the HMM approach, with the following parameters:

- **Data**: Daily NDVI and temperature time-series data with monthly aggregation.
- **Data points**: 12 points per year across 385 communes.
- **Hidden States**: 2 (representing different states of vegetation and temperature cycles).
- **Iterations**: **100** iterations for model training.
- **Year Range**: The analysis was conducted for data from 1987 onwards.

Key Features of HMMs:

- **Smoother Transitions:** Unlike Ruptures, which detects abrupt transitions, HMMs model gradual shifts between states, making them suitable for capturing seasonal transitions.
- **Probabilistic Uncertainty:** HMMs incorporate probabilistic uncertainty, improving robustness to noise and small fluctuations in data.
- **Continuous Adaptation:** HMMs adapt continuously to varying seasonal conditions, modeling dynamic changes in vegetation and temperature patterns over time.

Advantages of HMMs Over Ruptures:

- **Better Handling of Gradual Seasonal Transitions:** HMMs can capture progressive seasonal changes more effectively than Ruptures, which is limited to detecting abrupt shifts.
- **Reduced Sensitivity to Short-term Anomalies:** The probabilistic nature of HMMs makes them less sensitive to short-term anomalies, providing a clearer representation of long-term seasonal trends.
- **More Intuitive Representation:** HMMs offer a finer interpretation of vegetation and temperature cycles, such as accurately identifying the start and end of vegetation periods.

Comparison between Ruptures and HMM

Table 1: Comparison between Ruptures and HMM

Aspect	Ruptures	HMM (Hidden Markov Models)
Type of Transition	Abrupt transitions between segments.	Progressive transitions modeled by probabilities.
Segmentation	Divides into independent segments.	Associates each point with a hidden state, ensuring temporal continuity.
Underlying Model	No underlying model (deterministic approach).	Based on hidden states that influence observations.
Sensitivity to Noise	Sensitive to minor variations in the data.	Better handles noise through probabilistic modeling.
Robustness	Depends on the choice of parameters (cost, penalty).	Robust, automatically learns probabilities and transitions.
Interpretation	Limited to breakpoints (less intuitive for biological phenomena).	Provides a finer interpretation of states (e.g., start and end of vegetation).
Computational Complexity	Faster to calculate (especially for long time series).	More computationally expensive, especially for long series with many states.

Results of HMM Analysis

The application of HMMs provided a more refined understanding of seasonal trends: Vegetation cycles exhibited progressive changes instead of sudden shifts, supporting the hypothesis of climate-driven phenological shifts.

- Transitions between high and low vegetation periods were smoother, highlighting the limitations of abrupt segmentation methods like Ruptures.

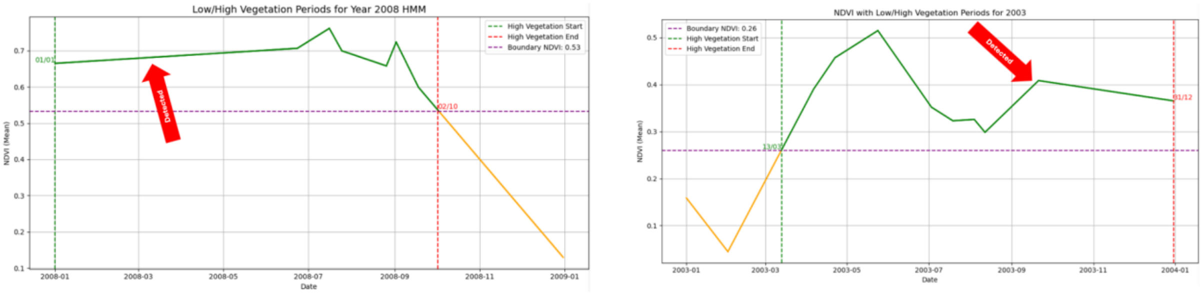


Figure 7: Improved Detection of Vegetation Periods with HMM

Figure 7 demonstrates the improved detection of vegetation periods using HMM, where transitions between high and low vegetation states are more gradual and aligned with actual seasonal changes. The figure illustrates how HMMs provide a clearer and more continuous model of vegetation dynamics compared to abrupt segmentation methods.

The application of HMMs improved the detection of transitions in vegetation cycles:

- **Accurate Detection of Transitions:** HMMs reliably detected the start and end of the high vegetation periods. For instance, in 2008 and 2003, the transitions were clearly marked, with the green dashed lines representing the start and the red dashed lines marking the end of the high vegetation periods.
- **Improved Sensitivity:** HMMs use hidden states and temporal continuity, which enabled the model to better capture subtle transitions and variations in the data compared to previous methods like Ruptures.

The use of HMMs to analyze vegetation periods across different years and communes provided valuable insights into the seasonal dynamics of high and low vegetation. This approach captured the gradual transitions between these periods, offering a more nuanced view compared to abrupt segmentation methods like Ruptures.

For instance:

- In 1988, the transition to high vegetation occurred in March, reaching its peak in November, with a boundary NDVI value of 0.43.
- In 2000, high vegetation began in February, peaked in May, and transitioned to low vegetation by January 2001, marked by a boundary NDVI value of 0.42.
- In 2014, high vegetation began in March, peaked around May, and declined to low vegetation in November, with a boundary NDVI of 0.46.
- In 2019, high vegetation started in March and ended in November, with a boundary NDVI of 0.47.

These consistent patterns across years demonstrate the adaptability of HMM to varying seasonal conditions.

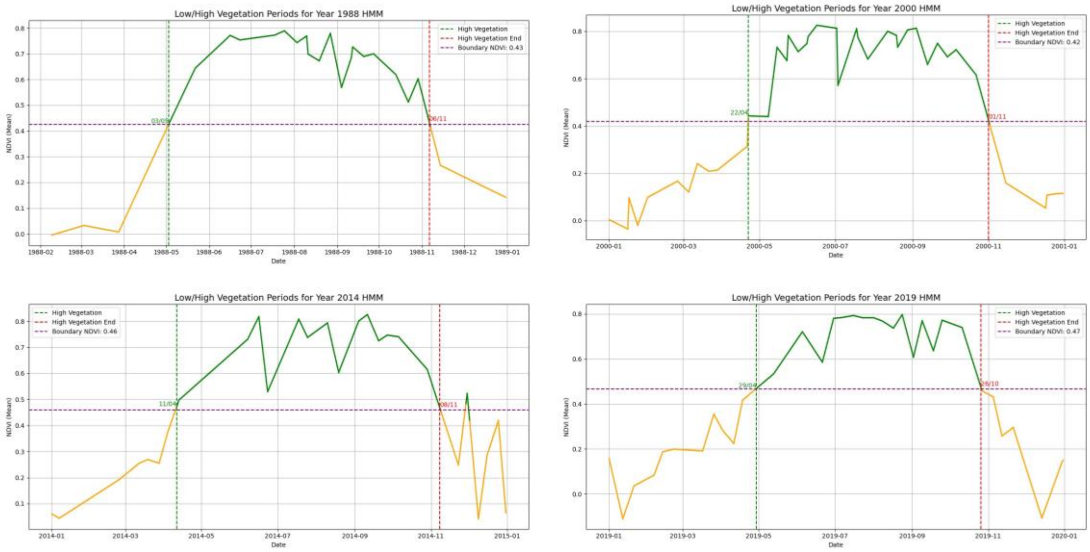


Figure 8: Segmentation Plots of Low/High Vegetation Periods for Evian (FR74001) using HMM

Figure 8 illustrates the HMM results for low/high vegetation periods in 1988, 2000, 2014, and 2019. The green dashed lines represent the start of high vegetation, while the red dashed lines mark the end of high vegetation. The boundary NDVI values are also shown, which help to identify the transition points in each year. The figure visually reinforces the gradual transitions detected by HMM, making it evident that the model effectively tracks seasonal changes over time, capturing both the start and end of vegetation phases.

These consistent transitions across various years support the idea of climate-driven changes in vegetation phenology, emphasizing how HMM provides a more refined and accurate model for seasonal trends.

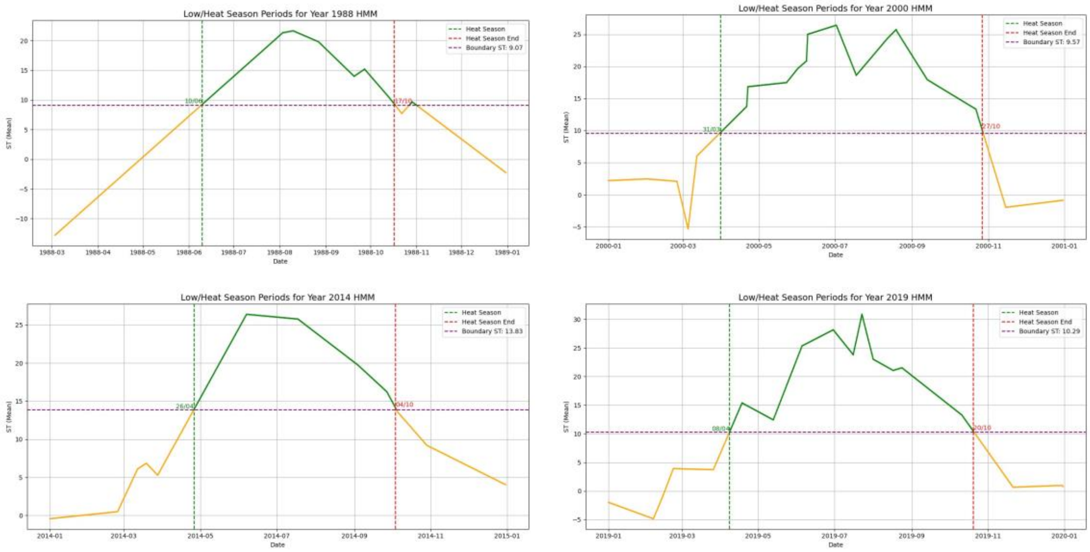


Figure 9: Segmentation Plots of Low/High Heat Periods for Evian (FR74001) using HMM

Figure 9 illustrates the HMM results for low/heat season for the same commune. The boundary temperature values (ST) are shown to highlight the transition points for each year. It reinforces the gradual transitions detected by HMM, emphasizing how the model effectively tracks temperature fluctuations over time, capturing both the start and end of the heat seasons.

The patterns observed across these years provide further evidence of climate-driven changes, complementing the trends seen in the vegetation analysis. In each case, HMM detected smooth transitions between low and heat seasons, illustrating its ability to capture subtle temperature variations. These consistent transitions in both vegetation and temperature cycles highlight the advantage of HMM in providing a more refined, continuous model of seasonal dynamics compared to abrupt segmentation methods like Ruptures. The combined analysis of vegetation and temperature underscores HMM's effectiveness in studying climate-driven shifts and their broader environmental impact.

The comparison between the NDVI and ST plots highlights the strong relationship between vegetation and temperature dynamics. Both sets of plots show similar seasonal patterns, with high vegetation phases (indicated by higher NDVI values) occurring during warmer periods, reflected in the temperature peaks on the ST plots. For instance, in 1988, 2000, 2014, and 2019, both NDVI and ST values rise in spring and early summer, corresponding to the high vegetation and heat season periods, respectively. The alignment of these peaks in both NDVI and ST plots demonstrates that warmer temperatures facilitate increased vegetation growth, supporting the idea of a close interaction between temperature and vegetation cycles.

5.3.2.3 Heatmap Visualization for Improved Representation

To further enhance the representation of seasonal dynamics, NDVI heatmaps were generated to visualize the variation in vegetation intensity over time. These heatmaps offer a powerful tool for understanding how vegetation activity changes throughout the year, providing insights into the temporal and spatial patterns of high and low vegetation phases. They also allow for a more nuanced view of vegetation intensity, highlighting the degree of vegetation growth, which is essential for assessing ecological health and environmental conditions.

The heatmaps provide a continuous view of both **NDVI** and **ST** variations, highlighting:

- **The duration of the high vegetation season (NDVI) and the heat season (ST)**: Both heatmaps show how the duration of these periods varies annually, allowing for detailed comparisons between years. The extremities of each year on the heatmaps correspond to the detected change points, marking the start and end of high vegetation periods and heat seasons. These variations provide a clear visual representation of how climate factors, particularly temperature, influence vegetation growth and activity. While the NDVI heatmap reflects the growing season's intensity, the ST heatmap shows how the heat periods align with temperature fluctuations, indicating how both vegetation and temperature cycles evolve over time.
- **Spatial differences in vegetation activity (NDVI) and temperature (ST)**: The NDVI heatmap highlights spatial differences in vegetation intensity across the study region, identifying areas of high and low vegetation activity. This allows for the detection of regions sensitive to climate change. Similarly, the ST heatmap reveals spatial temperature variations, showing how different areas experience more intense heat during certain months, which may influence vegetation growth. Together, these heatmaps provide a comprehensive view of how spatial variability in both vegetation and temperature affects ecosystems over time.
- **Gradual shifts in seasonal timing (NDVI and ST)**: Both the NDVI and ST heatmaps capture gradual shifts in the timing of high vegetation periods and heat seasons, offering further evidence of climate-driven changes. The heatmaps show earlier or later peaks in both NDVI and ST values, indicating shifts in vegetation growth cycles and temperature patterns. These shifts demonstrate the interconnected nature of vegetation and temperature dynamics, with temperature fluctuations influencing the timing and intensity of vegetation activity. The alignment of these changes in both indices emphasizes the role of temperature in driving shifts in vegetation phenology.

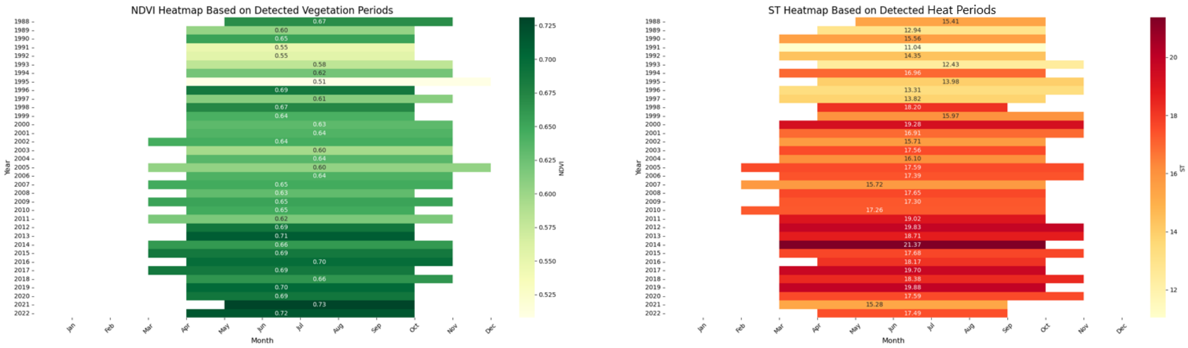


Figure 10: NDVI and ST Heatmap Representation

The heatmaps illustrate the spatiotemporal distribution of NDVI (for vegetation) and ST (for heat periods) across different years as can be seen in *Figure 10*. The NDVI heatmap provides a clearer picture of how the growing season has evolved, showing how the start, peak, and end of the high vegetation periods have shifted. The ST heatmap complements this by illustrating the temporal and spatial variation in temperature across the years, capturing the intensity of heat periods. The two heatmaps together emphasize the inter-connectedness of temperature and vegetation dynamics.

The NDVI heatmap represents vegetation intensity, with higher NDVI values indicating denser, healthier vegetation. The varying colors from light green to dark green reflect seasonal changes in vegetation activity. This allows for an easy comparison of how vegetation productivity has changed over the years. In contrast, the ST heatmap reveals the intensity of temperature changes during the heat periods, with higher temperatures (represented by the deeper red tones) occurring during the summer months. This highlights how temperature fluctuations correlate with the timing and intensity of the vegetation growing season.

Both heatmaps allow for a more granular analysis of vegetation and temperature changes across individual months. By visualizing these dynamics together, the heatmaps reinforce the findings from HMM analysis, showing not only the timing of transitions but also the intensity of these transitions in both vegetation and temperature. The heatmaps also reveal the shifts in both temperature and vegetation, allowing for an integrated view of how climate-driven changes are affecting the ecosystem.

By capturing both the temporal shifts and spatial patterns of vegetation intensity and temperature, the heatmaps provide a comprehensive view of how vegetation responds to long-term climate variability. The detected change points marking the start and end of both the high vegetation periods and the heat seasons further inform our understanding of the broader environmental impact of these shifts. The combined insights from both NDVI and ST heatmaps offer valuable tools for monitoring climate-induced changes and their ecological consequences.

This analysis has been conducted across all communes to examine shifts in vegetation and temperature dynamics, providing a comprehensive understanding of how climate-driven changes affect the region.

5.3.2.4 Discussion

In this study, we focused on analyzing the inter-annual variations of vegetation (NDVI) and temperature (ST) over time, employing a change point detection approach to identify key transition points in both vegetation and temperature cycles. By leveraging both Ruptures and Hidden Markov Models for change point detection, we sought to understand how shifts in these cycles are influenced by climate variability, ultimately providing insights into broader environmental changes.

The implementation of Ruptures allowed us to detect significant seasonal transitions, including the start and end of vegetation periods and heat seasons. However, as highlighted before, Ruptures struggled to detect transitions in certain years, where the onset or end of the vegetation period was missed. This limitation stems from the algorithm's sensitivity to abrupt changes and its inability to handle gradual shifts or anomalies in the data. In contrast, HMMs provided a more nuanced approach, allowing for the detection of smoother transitions between states, rather than relying solely on abrupt shifts. The incorporation of probabilistic uncertainty in HMMs made the model more robust to noise and data irregularities, which is particularly valuable when analyzing environmental datasets where subtle, gradual changes are common.

HMMs demonstrated significant advantages over Ruptures by capturing the gradual shifts in vegetation and temperature cycles, providing a more continuous and accurate representation of seasonal dynamics. This is evident from the results, where HMMs reliably detected the start and end of the high vegetation periods and heat seasons, even in years with less pronounced transitions. The application of HMMs across multiple communes further reinforced the robustness of this approach, showing its ability to adapt to varying climatic conditions, thus offering a clearer understanding of the shifts in both vegetation growth and temperature over time.

One of the key findings of this study is the interconnected nature of vegetation and temperature dynamics. The comparison between NDVI and ST heatmaps clearly illustrates the close relationship between vegetation cycles and temperature fluctuations. Higher NDVI values, indicating high vegetation periods, generally align with warmer temperatures, reflecting the critical role that temperature plays in driving vegetation growth. The heatmaps also highlighted spatial differences in vegetation intensity across communes, revealing regions that are more sensitive to climate variability. These insights are crucial for understanding the potential ecological consequences of climate change on vegetation patterns, as different regions may experience varying levels of vulnerability to shifting climate patterns.

The NDVI and ST heatmaps, which were generated for the same communes, provided a comprehensive view of how vegetation and temperature dynamics change over time. These heatmaps offered not only a visual representation of the timing and intensity of transitions but also a way to capture the gradual shifts that occur over multiple years. By incorporating both NDVI and ST data, we were able to capture how both vegetation and temperature fluctuate across the year, with each commune displaying unique seasonal dynamics. These heatmaps provided insights into the timing of high vegetation and heat seasons, identifying shifts that may indicate longer-term climate-driven trends. Furthermore, the analysis of spatial variability in both indices helped us identify regions that may be more resilient or sensitive to temperature fluctuations, providing valuable insights for ecological management and climate adaptation strategies.

In summary, the use of both Ruptures and HMMs to detect seasonal transitions in NDVI and ST data provided a powerful methodology for understanding how vegetation and temperature dynamics have shifted over time. While Ruptures offers a faster and more straightforward approach for detecting abrupt transitions, HMMs excel at capturing gradual, climate-driven shifts, providing a more detailed and accurate representation of seasonal dynamics. By conducting this analysis across multiple communes, we were able to gain a deeper understanding of how climate variability impacts ecosystems, paving the way for further research into the long-term effects of climate change on vegetation phenology and ecosystem health.

However, the study is limited by potential data inconsistencies and missing values in certain periods, particularly in the winter months. The lack of winter data and the need for interpolation affected the accuracy of detecting the beginning of the vegetation and temperature cycles, particularly for early seasonal transitions. This limitation applies to both Ruptures and HMMs, as both approaches struggled to accurately identify the start of the high vegetation periods and heat seasons due to the absence of critical winter data. This limitation should be considered when interpreting the results, as it may introduce some uncertainty into the detected change points, especially in years with less robust data.

5.3.3 Intra-Segmentation Approach

The goal of intra-segmentation is to refine the identification of change points within a given environmental event by focusing on more localized and short-term variations. While broader segmentation techniques like those used in the inter-annual approach are valuable for identifying major transitions (e.g., the start and end of high vegetation periods or heat seasons), intra-segmentation offers a more granular view. It allows us to zoom in on smaller, more specific shifts that may occur within those larger transitions. This refined approach helps us better understand the nuances of environmental events, capturing the subtler fluctuations that could have significant ecological implications. In particular, intra-segmentation enables the identification of secondary shifts, such as the intensification of drought conditions or post-event recovery periods, which may not be visible in broader seasonal trends. By focusing on the finer-scale dynamics of environmental change, we can achieve a more detailed and comprehensive understanding of the causes and consequences of these shifts.

5.3.3.1 Methodology

To achieve intra-segmentation, we employed the Ruptures algorithm with the PELT (Pruned Exact Linear Time) method, which efficiently partitions the time series into segments by detecting abrupt shifts in statistical properties. The PELT method is particularly effective for identifying change points while optimizing computational resources, making it ideal for detecting secondary shifts within seasonal transitions.

- **Input:** NDVI and temperature time series data, aggregated over the summer months (JJA) (June, July, August). This seasonal focus allows for a more accurate detection of changes occurring during the peak growing season and heat periods.

- **Penalty:** A controlled penalty parameter (pen=3) that helps balance the sensitivity of the algorithm to change points. By fine-tuning the penalty, we maintain a trade-off between capturing significant changes and avoiding overfitting, ensuring that we detect important shifts without excessive segmentation.
- **Number of Breakpoints:** The segmentation process is designed to detect multiple breakpoints within the time series, focusing on smaller sub-events such as drought intensifications, sudden temperature spikes, or post-event recovery phases that might occur within the broader seasonal cycles.

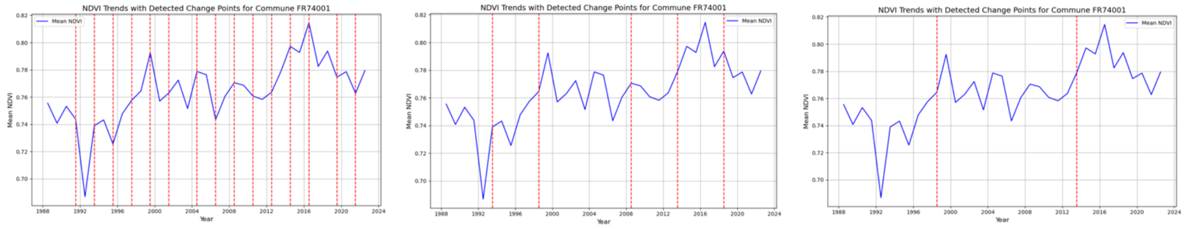
This methodology allowed us to segment the broader transitions into more localized fluctuations, such as brief periods of environmental stress, temporary disruptions in vegetation cycles, or sudden shifts in temperature. The finer granularity enabled by PELT gave us the ability to capture secondary environmental shifts that would have otherwise been missed in broader segmentation frameworks. For example, during the high vegetation period, we could detect smaller-scale events such as short-lived drought intensifications that might cause temporary stress on vegetation or even identify post-event recovery as the vegetation begins to bounce back from a climatic anomaly.

The application of intra-segmentation helps us track rapid environmental changes that are not immediately evident in long-term trends, providing a better understanding of how environmental factors, such as temperature and precipitation, interact and influence each other on shorter timescales. By detecting these secondary shifts, we gain insights into both short-term fluctuations and longer-term seasonal trends, offering a more comprehensive picture of how climate variability impacts ecosystems.

Through this approach, we can break down major transitions into smaller, more manageable sub-events, enabling us to identify the underlying causes behind specific ecological shifts. This detailed analysis not only improves our understanding of how ecosystems respond to immediate disturbances but also contributes to developing better management practices and climate adaptation strategies.

5.3.3.2 Choice of Penalty Value

In the intra-segmentation approach, the penalty parameter controls the sensitivity of the segmentation algorithm, balancing between detecting significant change points and avoiding over-segmentation. The penalty value essentially dictates the trade-off between the granularity of the segmentation and the risk of detecting too many insignificant changes.



Pen = 1 **Pen = 3** **Pen = 10**

Figure 11: Detected Change Points at Varying Penalty Values

Based on the results shown in *Figure11*, the following penalty settings were tested:

- **Low Penalty (Pen = 1):** In the first scenario, where the penalty is set to 1, the segmentation algorithm is highly sensitive to changes. This results in over-segmentation, where nearly every minor fluctuation in the NDVI time series is treated as a change point. The number of detected transitions is high, capturing even the smallest local variations in the data. While this can provide an extremely detailed view of environmental dynamics, it leads to a large number of detected change points that might not reflect significant ecological shifts, potentially introducing noise. This setting is better suited for scenarios where detecting every slight fluctuation is crucial, but it may be less useful for identifying broader, long-term trends.
- **Moderate Penalty (Pen = 3):** In the second scenario, with a moderate penalty of 3, the algorithm detects a more balanced number of change points. The segmentation still captures multiple transitions but avoids over-segmentation, ensuring that it identifies key shifts in the data while reducing noise. The detected change points correspond to the major environmental transitions such as the onset and end of high vegetation periods and temperature fluctuations, which are crucial for understanding the broader seasonal dynamics. This penalty value strikes a good balance, ensuring that the segmentation is sensitive to meaningful shifts without being overly detailed. This setting is ideal for capturing both localized fluctuations and major seasonal trends.
- **High Penalty (Pen = 10):** With a high penalty of 10, the algorithm becomes more stringent, resulting in fewer detected change points. The segmentation focuses on only the largest, most significant transitions, often smoothing over smaller variations in the data. This approach is beneficial for identifying long-term, major shifts in environmental trends, such as the overall trajectory of vegetation growth or temperature patterns, but it misses smaller, short-term fluctuations. While this approach reduces noise and over-segmentation, it may not be as useful for detecting secondary events like brief drought intensifications or post-event recovery periods, which could be crucial for certain analyses.

The selection of penalty = 3 in our analysis strikes an optimal balance between detecting significant changes and avoiding over-segmentation. This penalty setting captures key environmental shifts, such as transitions between high and low vegetation periods, while maintaining a manageable number of change points. It provides a clear view of long-term trends while still being sensitive to short-term variations, making it appropriate for understanding broader climatic impacts on ecosystems.

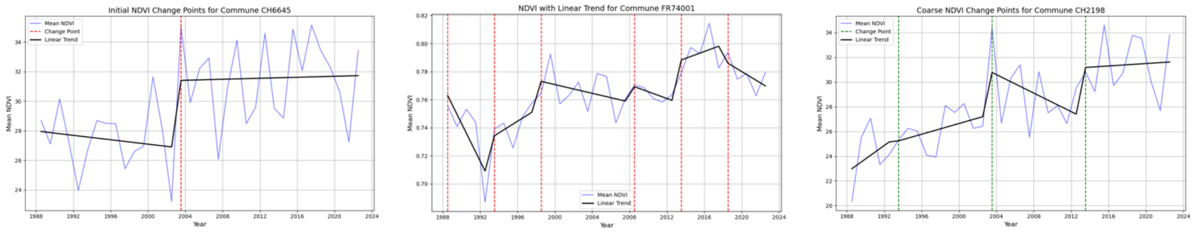


Figure 12 : NDVI Trends with Detected Change Points

The results demonstrate how the Ruptures algorithm effectively detects NDVI change points across different communes, providing insights into the variations in vegetation trends over time. By adjusting the penalty parameter, the algorithm can capture both subtle fluctuations and significant shifts in vegetation dynamics. A low penalty detects multiple, finer changes, while a high penalty focuses on more pronounced transitions, highlighting broader trends. The inclusion of linear trends in the analysis allows for the observation of long-term vegetation trajectories, often showing an overall increase in NDVI after detected change points. These trends suggest that, in general, vegetation has been improving over time, likely due to positive environmental or climatic factors. Overall, the results showcase how change point detection, combined with linear trend analysis, provides a nuanced view of vegetation dynamics, revealing both short-term fluctuations and long-term trends across different regions (*Figure 12*).

5.3.3.3 Results

The analysis of NDVI and ST change points across communes reveals several common years where significant shifts in vegetation and temperature occurred. The bar plots for both NDVI and ST show distinct patterns in terms of the years with the most frequent change points, which can help in identifying periods of environmental or climatic significance.

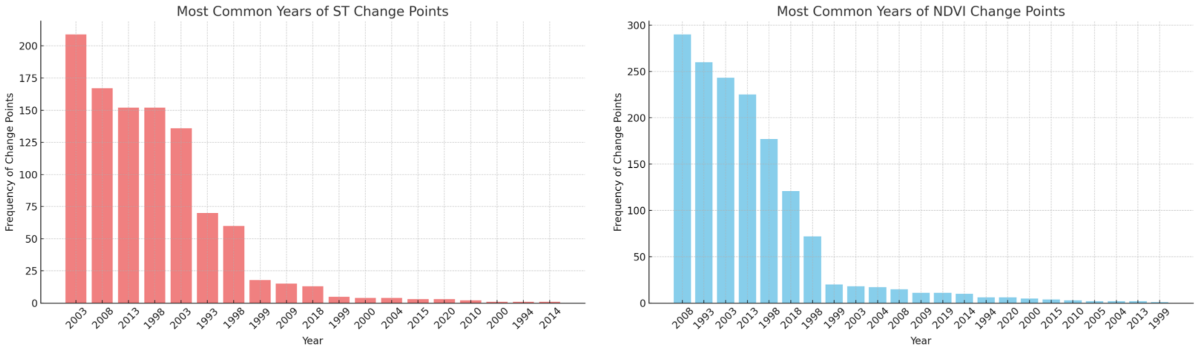


Figure 13: Most Common Years of ST and NDVI Change Points Across All Communes

For NDVI (vegetation), the most frequent change points were observed in the years 2008, 1993, and 2003. This suggests that those years experienced notable shifts in vegetation dynamics, which could be due to varying climatic conditions such as temperature fluctuations, precipitation patterns, or other environmental factors that influenced vegetation growth during those periods. The peak in 2008 is particularly interesting, as it appears to coincide with a period of global climate anomalies, which might have affected vegetation growth in specific regions.

For ST (temperature), the common years identified are similar, with 2003, 2008, and 2013 showing the highest frequency of detected change points. These years correspond to significant temperature shifts, which likely had a direct impact on vegetation health. Notably, 2003 stands out as a year with frequent change points in both indices, indicating that both vegetation and temperature underwent substantial changes during this time. The year 2008, which also appears prominently in the NDVI analysis, reflects a notable climate event that may have been related to an extreme temperature anomaly.

When comparing the years with common change points for both NDVI and ST, we observe that 2003 and 2008 are particularly significant. In 2003, both vegetation and temperature experienced major shifts, possibly due to extreme climatic events such as heatwaves or droughts. These events could have caused stress in vegetation, as seen in the vegetation change point data. Similarly, 2008 also appears as a critical year for both indices, likely reflecting a period of rapid environmental change, which could be linked to both regional and global climatic anomalies that affected temperature and vegetation growth patterns.

Interestingly, 2013 appears prominently for ST but less so for NDVI. This discrepancy suggests that while temperature may have experienced shifts that year, the effect on vegetation was either less pronounced or more gradual, which could indicate different regional responses to climatic events or variations in local environmental conditions.

5.3.3.4 Discussion

The comparison of the most common years of detected NDVI and ST change points demonstrates the strong interaction between temperature fluctuations and vegetation dynamics. 2003 and 2008 emerge as critical periods of significant change across both indices, likely reflecting major climatic events, such as heatwaves, droughts, or other extreme weather patterns that have a profound impact on ecosystems. 2003, in particular, aligns with the European heatwave, which affected many parts of Europe, leading to drastic temperature anomalies and environmental stress that likely caused shifts in both vegetation dynamics and temperature patterns during that year.

The clear correspondence between temperature anomalies and shifts in vegetation patterns during these years emphasizes the need for a deeper understanding of how temperature impacts vegetation growth, particularly in response to extreme climate events, such as the 2003 European heatwave. The heatwave exacerbated the climate stress on vegetation, resulting in altered growing seasons and affecting vegetation health and productivity.

The findings from both NDVI and ST analyses support the hypothesis that temperature variability is a key driver of vegetation dynamics. This underscores the importance of long-term monitoring and climate data analysis to identify shifts in ecosystem health, enabling more effective climate adaptation strategies. The use of change point detection methods, such as Ruptures and PELT, proves invaluable in identifying both large-scale seasonal transitions and smaller-scale fluctuations within those periods. By examining both long-term trends and short-term shifts, we can gain a more comprehensive view of how climate variability affects ecosystems, ultimately informing management practices and guiding climate resilience efforts.

6. Conclusion

This study provided a detailed analysis of vegetation and temperature dynamics in three diverse regions (Geneva, Evian, and Fribourg) through the application of advanced change point detection methodologies: the Ruptures algorithm and Hidden Markov Models. By analyzing time-series data for NDVI and temperature, we were able to identify key transition points and trends that characterize the seasonal and inter-annual changes in these environmental variables.

Our findings reveal significant correlations between vegetation growth (NDVI) and temperature, demonstrating that warmer temperatures tend to extend growing seasons and enhance vegetation productivity. These insights are crucial for understanding the broader implications of climate change on ecosystems, particularly in the context of urbanization, water availability, and altitude-related variability.

The comparison between the Ruptures and HMM methods highlighted their respective strengths and limitations. Ruptures proved effective for detecting abrupt changes, but struggled in capturing subtle, gradual shifts or dealing with data anomalies. In contrast, HMMs provided a more robust framework for modeling gradual transitions, making them ideal for capturing the continuous dynamics of vegetation and temperature cycles, and offering deeper insights into climate-driven changes.

Additionally, the use of spatial heatmaps enabled a more nuanced understanding of how vegetation intensity and temperature fluctuations vary over time and space. These visualizations underscore the importance of considering both temporal and spatial dimensions when assessing the impact of climate variability on ecosystems.

Ultimately, this study contributes valuable knowledge to the understanding of how climate variability influences vegetation cycles, providing a foundation for more targeted climate adaptation strategies. The combination of both Ruptures and HMMs offers a comprehensive approach to environmental change detection, facilitating more accurate predictions of future trends and supporting effective ecosystem management.

Future research should focus on addressing the limitations of data quality, particularly for winter months, where sensor limitations often lead to gaps in the dataset. To overcome this, robust imputation techniques using advanced machine learning approaches could be employed to predict missing values with greater precision. Additionally, further exploration of integrating additional environmental indices, such as water and glacier dynamics, would provide a more comprehensive understanding of the interactions between climate variables. By expanding the temporal and spatial scope of the study, including data from more regions and a broader time range, this work can offer even deeper insights into the broader environmental changes associated with climate change, enabling more accurate predictions and informed climate adaptation strategies.

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