Details of the dataset

From example outputs from NASA's Land Information System (LIS), several variables (daily) are simulated for the upper part of Thailand:

- Terrestrial Water Storage (TWS)
- Soil Moisture (SM)
- Streamflow

Aspects

Present the findings from the data related to climate, water, and agriculture. The analysis can be helpful to support the agriculture sector.

Consider a drought index for the decision support system as an example. Instead of providing the time series, classify them into a few levels, such as 0 = normal, 1 = potential risk, 1 = high danger, and so on, how utilizing them helps to support those sectors.

1. Compute and display long-term trends (e.g., mm/year) of each variable.
2. Extract streamflow at gauge location, so we can evaluate them later.
3. Create a basin-average time series (daily from 2010 to 2023) over key river basins.
4. Display the time series of the basin and decide how to use it for decision support (with respect to, e.g., water, climate, agriculture, and disaster).

Steps

Identifying and assessing the risk of drought involves analyzing various environmental and climatic variables to understand their impact on drought conditions. Here's a structured approach to identifying drought risk, integrating the analysis methods:

1. Data Collection and Preparation

Variables:

- **Soil Moisture (SM)**: Indicates the amount of water in the soil, critical for understanding drought conditions.
- **Terrestrial Water Storage (TWS)**: Reflects the total water stored in the soil, snow, and surface water.
- **Streamflow (SF)**: Measures the flow of water in rivers and streams, which is crucial for understanding water availability.

Data Preparation Steps:

- **Normalize** the data to bring all variables onto a comparable scale.
- **Aggregate** the data to the desired time intervals (e.g., yearly or monthly) for trend analysis.

2. Trend Analysis

Methods:

- **Mann-Kendall Trend Test**: Identifies monotonic trends in time series data to assess if there are significant trends in soil moisture, streamflow, and TWS over time.
- **Seasonal Decomposition**: Breaks down time series data into trend, seasonal, and residual components to analyze seasonal patterns and long-term trends to isolate seasonal variations from long-term trends and identify patterns that may indicate increasing or decreasing drought risk.

3. Frequency Analysis

Cross-Wavelet Transform (CWT):

- **Analyze Temporal Patterns**: CWT helps to identify the scale (frequency) at which the power is high, indicating predominant periodicities or cycles in the data.
- **Cross-Wavelet Transform (XWT)**: Evaluates the relationship between two time series (e.g., soil moisture and streamflow) and how their interactions change over time.

4. Risk Assessment

Techniques:

- **Compute Soil Moisture Index (SMI)**: Provides an indicator of soil moisture conditions relative to a historical baseline, useful for assessing drought risk.
- **Assess Changes in CWT**: Determine how changes in wavelet power spectra relate to drought conditions to determine if there are shifts in frequency components that correlate with known drought periods.

5. Decision-Making for Drought Classification

Considerations:

- **Combine Insights** from trend analysis, frequency analysis, and risk assessment to get a comprehensive view of drought risk.
- **Identify Key Patterns** and significant changes in variables that align with known drought events.
- **Develop Drought Risk Maps** using the insights gained from the analysis. Highlight regions and periods of high risk based on soil moisture, TWS, and streamflow data.
- **Update Management Strategies** based on identified risk patterns. Implement measures to mitigate drought impacts, such as water conservation strategies or adjustments in agricultural practices.

Procedure

1. **Data Collection and Preparation.**
   i. **Preprocess the Dataset:**
   Analysis variables by the automate code generate statistics and visualize and be used for new data arrives.
      i. Check files and load the datasets
      ii. Check variables, dimensions, and attributes dataset
      iii. Extract relevant variables (example SM, TWS, streamflow).
      iv. Compute basic statistics (min, mean, max, standard deviation)
   ii. **Convert the xarray dataset into numpy arrays.**
      i. Use Python libraries like xarray, numpy, matplotlib, and pandas for analysis.
      ii. Create visualizations (e.g., heatmaps, time series plots) to represent the findings
   iii. **Flatten the spatial dimensions for correlation analysis**
      i. Combine into a DataFrame for correlation,
      ii. Mean across spatial dimensions
      iii. Compute the correlation matrix
      iv. Visualize the correlation matrix

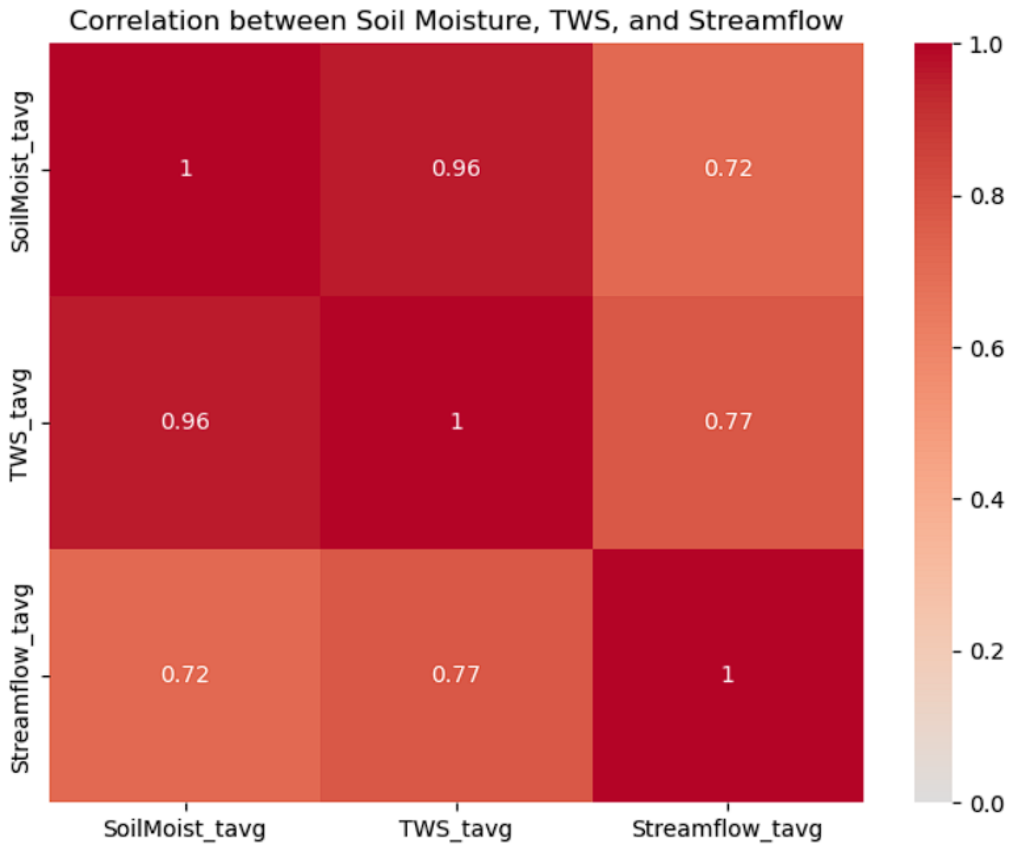

Figure 1 Correlation analysis between soil moisture, terrestrial water storage (TWS), and streamflow

To draw meaningful conclusions from correlation analysis between soil moisture, terrestrial water storage (TWS), and streamflow, let's consider a few aspects of interpreting the results:

1. Correlation Matrix Values: The correlation matrix will contain values between -1 and 1:

- Positive Correlation (0 to 1): A positive value indicates that as one variable increases, the other tends to increase as well.
- Negative Correlation (-1 to 0): A negative value means that as one variable increases, the other tends to decrease.
- Zero Correlation (~0): No linear relationship between the variables.

2. Conclusion Scenarios

- Scenario 1: Strong Positive Correlation (e.g., 0.7-0.9): Soil Moisture & TWS: suggests that higher soil moisture is typically associated with greater overall terrestrial water storage.
- Scenario 2: Weak or No Correlation (e.g., 0.0-0.3): Soil Moisture & Streamflow: suggests that soil moisture variations do not strongly influence streamflow in the region. This could occur if local streamflow is more influenced by other factors (e.g., upstream conditions or direct rainfall).
- Scenario 3: Negative Correlation (e.g., -0.4 to -0.7): TWS & Streamflow: may indicate that during periods of increased terrestrial water storage (e.g., when water is held in soil or aquifers), streamflow decreases. This could happen in regions where water is absorbed into the ground rather than flowing to rivers immediately.

iv. Plot variable with the time series, Calculate statistics over the specified spatial dimensions

i. Aggregate or resample data as needed (e.g., daily to monthly averages).
ii. Plot variable statistics (min, mean, max, standard deviation)
iii. Trend Component: Use to analyze long-term changes and overall direction.
iv. Seasonal Component: Identify recurring patterns and plan accordingly.
v. Residual Component: Detect anomalies or noise.

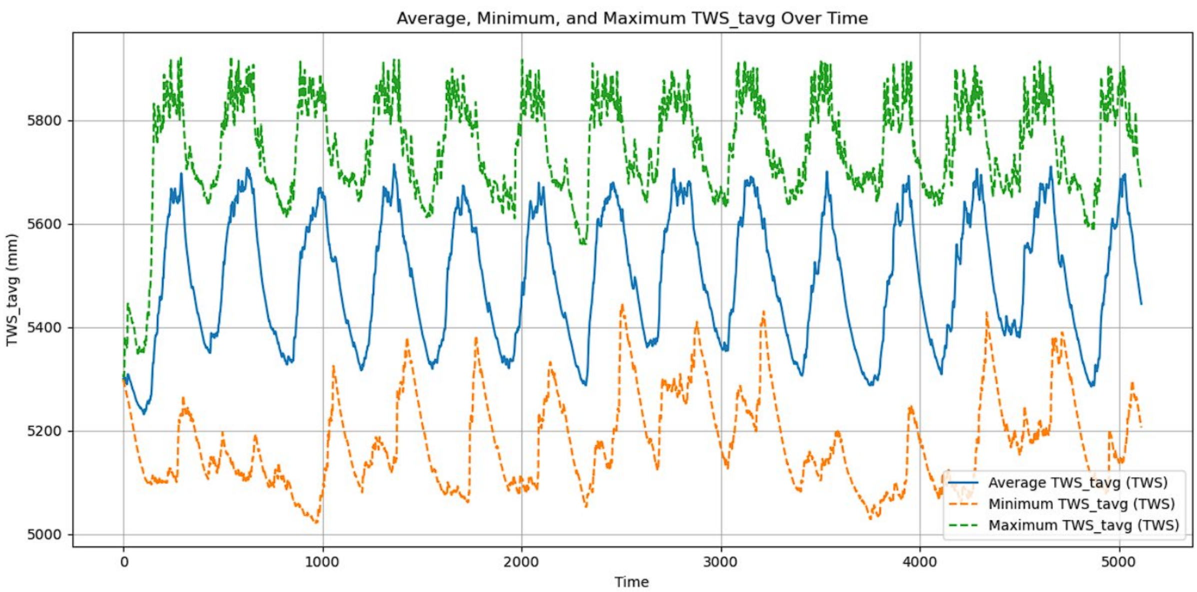

Figure 2 Calculation of statistics TWS variable over the specified spatial dimensions

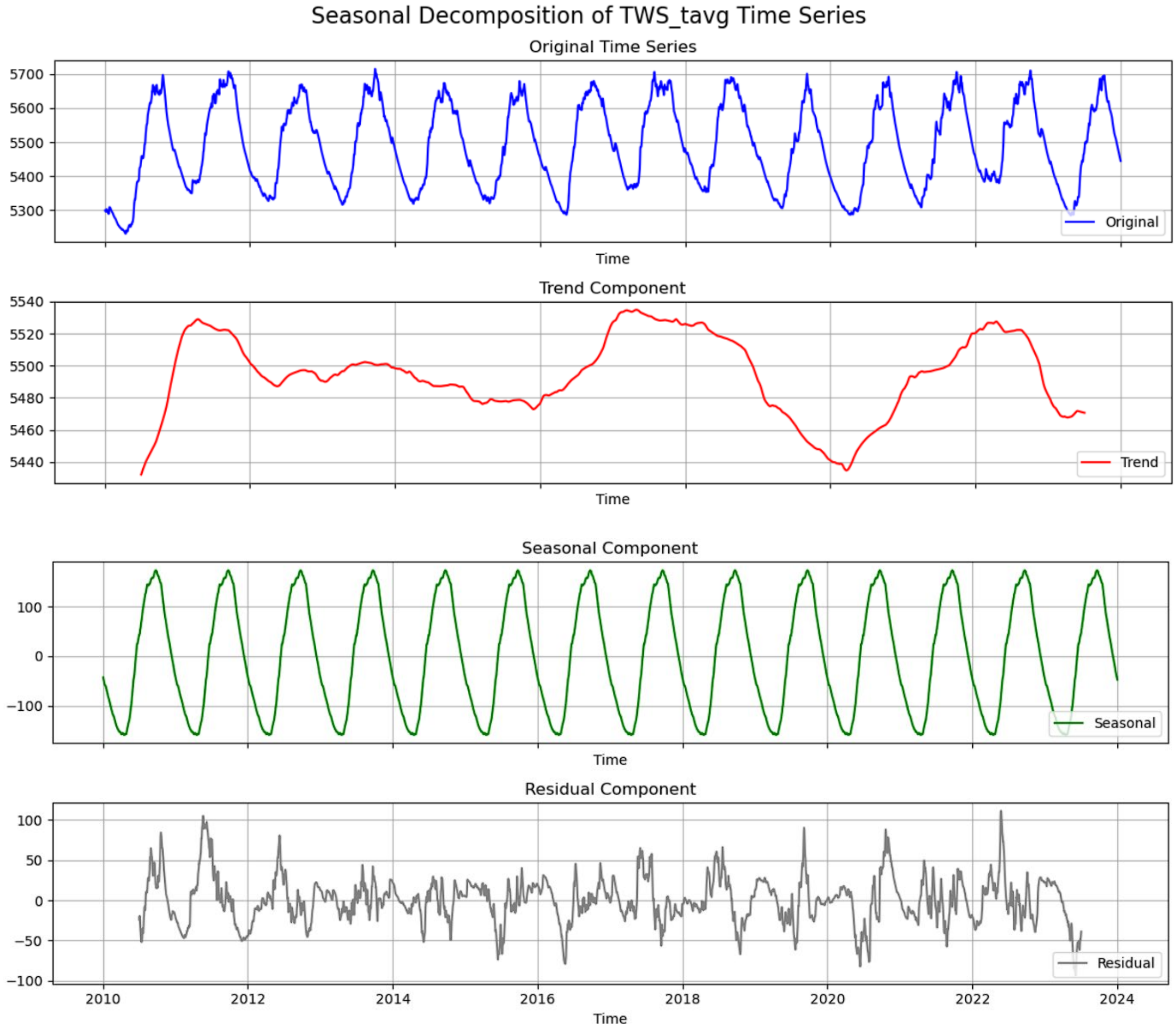

Figure 3 Seasonal decomposition of TWS over the spatial dimensions to get the overall time series

Summary

- Trend Component: Use to analyze long-term changes and overall direction.
- Seasonal Component: Identify recurring patterns and plan accordingly.
- Residual Component: Detect anomalies or noise.
- Use decomposed components to improve Modeling and Forecasting performance.

2. **Trend Analysis**

   Calculate trends (e.g., mm/year) for each variable over the given period.

   i. **The Standardized Soil Moisture Index (SSI)** is a z-score, indicating how many standard deviations that a SMAP value is from the historic mean.

ii. **The standardized soil moisture anomaly (SMA)** the long-term modelled soil moisture and revealed strong negative values during well-known drought periods in the region.

iii. Plot the trend maps for visualization.

The impacts of **SSI** on drought detection in the region using cross-wavelet analysis. This technique enables the calculation of correlation between two time series taking into account lagged relationships. This is especially useful to assess the impact of soil moisture deficit due to the delay in plants to respond to water stress in the soil.

iv. Analysis describes the general change in a variable with time.

- **Trend Analysis**: Perform trend analysis using statistical tests (e.g., Mann-Kendall) or regression models to detect significant changes over time.
- **Sen's Slope Estimator**: This can complement the Mann-Kendall test by quantifying the rate of change (slope) of a trend over time, giving a clearer understanding of the magnitude of change even if it's not statistically significant.
- **The Theil-Sen estimator** is a robust statistical method used for estimating the slope of a trend line, particularly in time series data. It is less sensitive to outliers compared to ordinary least squares (OLS) regression, making it ideal for datasets with noise or non-normal distributions.
- **Seasonal Decomposition of Time Series (STL Decomposition)**: This technique can help break down your SSI data into trend, seasonal, and residual components, offering a clearer picture of long-term changes and cyclical drought patterns.
- **Spatiotemporal Visualization:** Create visualizations to display the spatiotemporal changes in drought conditions.

Conclusion

1. STL Decomposition of Soil Moisture:

i. **Trend Component**:

- The trend component provides insight into the long-term direction of soil moisture over the analysis period.
- If the trend shows a consistent increase, it indicates a gradual rise in soil moisture levels, which might be due to changes in precipitation patterns, irrigation practices, or other hydrological factors.
- Conversely, a declining trend suggests decreasing soil moisture, which could indicate drought conditions, increased evaporation, or less rainfall.

ii. **Seasonal Component**:

- The seasonal component captures recurring patterns in the soil moisture data, reflecting regular seasonal variations.

- A strong seasonal cycle typically indicates that soil moisture is highly influenced by seasonal factors such as rainy and dry seasons, temperature fluctuations, and vegetation growth cycles.
- Understanding these seasonal changes is crucial for agricultural planning, water resource management, and predicting droughts.

iii. **Residual Component**:

- The residual component represents random noise or irregular variations that are not explained by the trend or seasonal components.
- High variability in the residual component might indicate short-term events affecting soil moisture, such as sudden rainfall, irrigation, or extreme weather conditions.
- Low residuals suggest that the trend and seasonality explain most of the variations in the data, which implies more predictable soil moisture dynamics.

iv. Overall Interpretation:

- The STL decomposition provides a detailed view of soil moisture dynamics by separating the data into meaningful components.
- A stable or increasing trend could suggest favorable conditions for agriculture, whereas a declining trend may raise concerns about drought risks.
- Seasonal patterns highlight the need to adapt water management strategies according to predictable seasonal cycles.
- Understanding these components allows stakeholders to make informed decisions on agricultural practices, water conservation, and planning for extreme weather conditions.

2. SSI Interpretation

The SSI provides a standardized measure of soil moisture conditions relative to historical norms to interpret different ranges of **SSI values**:

- **SSI > 2**: Extremely wet conditions.
- **SSI between 1 and 2**: Moderately wet conditions.
- **SSI between 0 and 1**: Slightly wetter than average.
- **SSI between -1 and 0**: Slightly drier than average.
- **SSI between -2 and -1**: Moderately dry conditions, which could indicate early signs of drought.
- **SSI < -2**: Extremely dry conditions, indicative of severe drought.

The Standardized Soil Moisture Index (SSI) is a z-score that represents deviations of soil moisture from its historical average. SSI values indicate the severity of wet or dry conditions, providing a standardized measure across time and space.

Positive SSI values indicate wetter-than-average conditions, while negative values signify drier-than-average conditions. Extreme values (e.g., SSI ≤ -2 or SSI ≥ 2) point to significant anomalies, often corresponding to droughts or floods.

i. **Key Findings:**

- Spatial Patterns: SSI visualizations reveal distinct spatial variations in soil moisture across the study region, highlighting areas prone to moisture deficit or surplus. Regions with consistently low SSI values are likely to face drought conditions, impacting water availability and agricultural productivity.
- Temporal Trends: Temporal analysis of SSI across multiple time steps indicates fluctuating moisture conditions, with clear patterns corresponding to known dry and wet periods in the historical record. Persistent negative SSI values often align with drought events, validating SSI as a reliable drought detection tool.
- Yearly Changes: Yearly aggregations of SSI show how moisture levels have evolved over time, capturing both short-term variability and long-term trends. This helps in assessing the impact of changing climate patterns on soil moisture dynamics in the region.

ii. **Visual Summary and Communication**

Use visual aids like SSI maps, time series plots, or animated sequences to clearly communicate your findings. These can help stakeholders quickly grasp the spatial extent and severity of moisture anomalies.

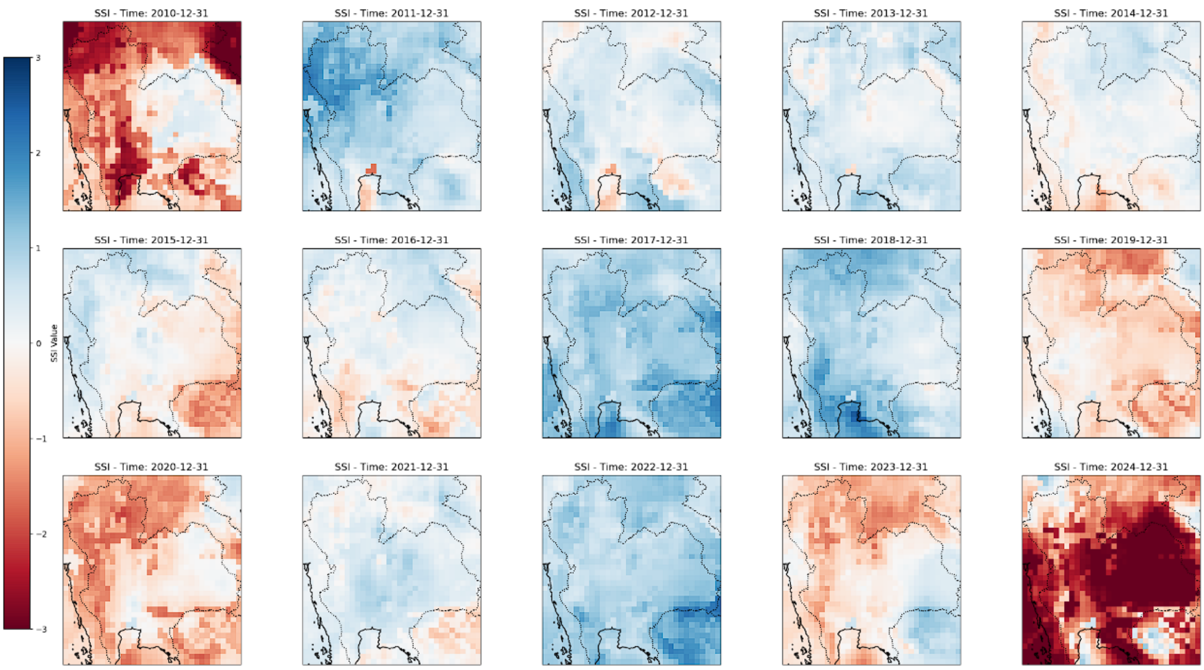

Figure 4 Displays the plot with SSI data for yearly time step

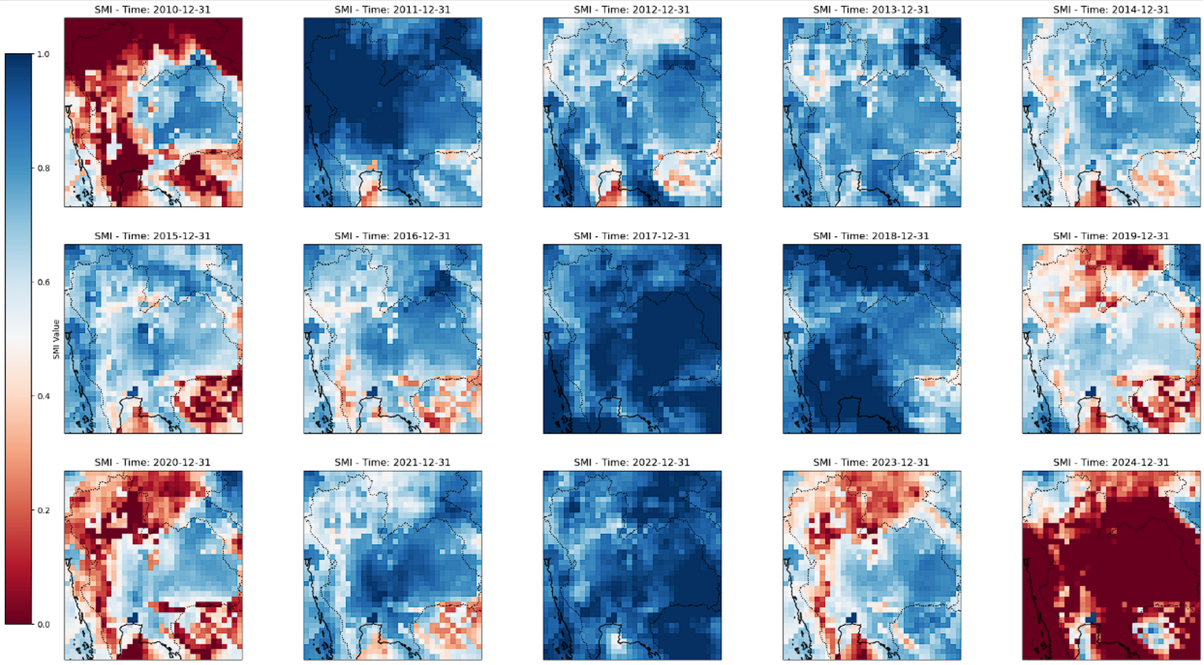

Figure 5 Displays the plot with SMI data for yearly time step

Compare the Standardized Soil Moisture Index (SSI) and the Soil Moisture Index (SMI)

- SSI is suited for detecting extreme moisture conditions, providing a relative measure of how unusual current conditions are based on historical data. It's suitable for applications that require an understanding of how rare or extreme current conditions are.
- SMI provides a quick and simple way to assess soil moisture, scaling it between predefined bounds of historical extremes. When just need to know if it's wetter or drier than usual.

3. **Cross-Wavelet Transform (CWT) for Impact Analysis:**

- The Continuous Wavelet Transform (CWT) analysis revealed significant periodic patterns in the SSI data at specific frequencies. Peaks in the wavelet power indicate dominant cycles, such as annual or semi-annual periods, which can be linked to seasonal or recurring drought conditions in the region.
- By analyzing multiple grid points, the CWT highlighted variations in SSI patterns across different locations. Areas with strong periodic signals may indicate regions that are more prone to consistent drought conditions or have distinct seasonal soil moisture dynamics.

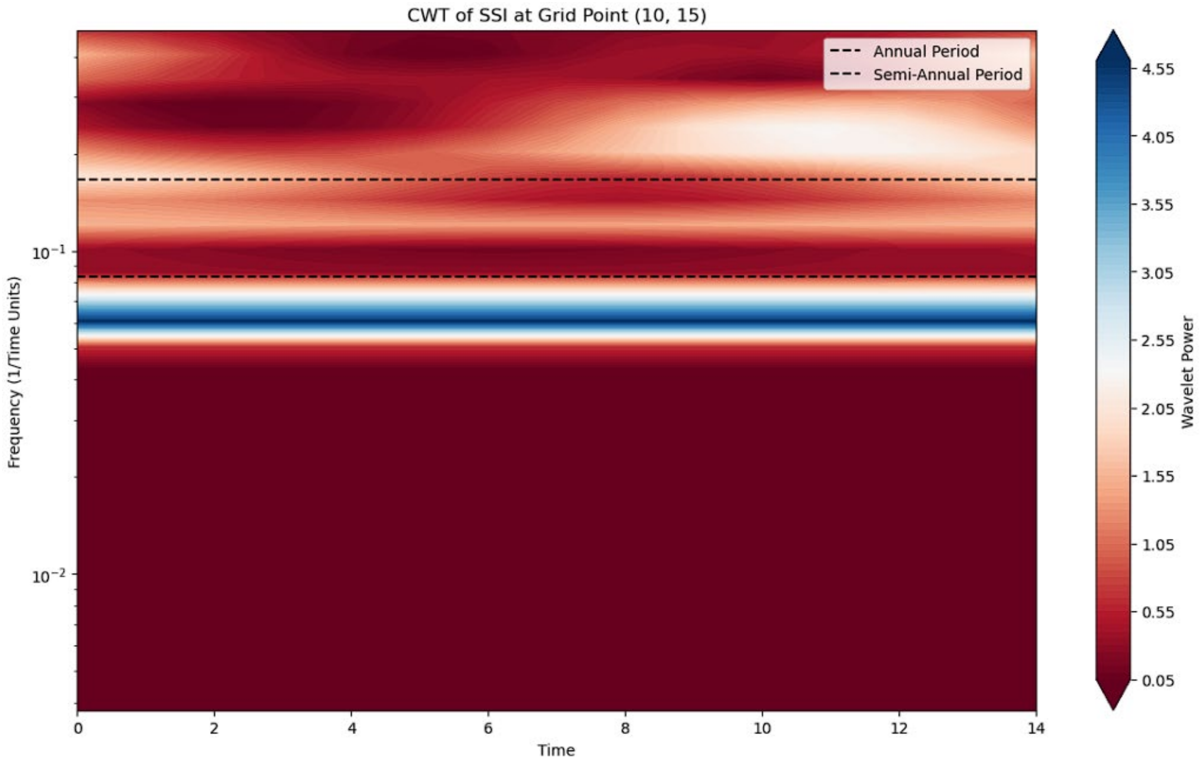

Figure 6 Compute and plot the Continuous Wavelet Transform (CWT) of the SSI data

4. **Decision-Making Insights:**

- **Identify Recurring Drought Patterns**: Use detected periodicities to anticipate recurring drought conditions.
- **Understand Time-Lagged Effects**: Analyze the time-lagged relationships to understand how soil moisture deficits may impact crop health over time.

Next Steps:

- **Validation**: Use additional datasets (e.g., satellite data, field measurements) to validate the trends and patterns observed in the soil moisture data.
- **Advanced Modeling**: Explore predictive models (e.g., machine learning) to forecast and enhance drought prediction capabilities.
- **Policy Implementation**: Use the insights from the analysis to inform policy and guide resource management decisions, focusing on regions identified as high risk for drought.