**Exploring the interplay of Drought and Nitrogen Use Efficiency in Winter Wheat: Insight and Adaptive strategies in Freising, Bavaria**

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**Abstract**

Climate change and weather patterns exert considerable influence on drought levels, Germany was identified as the third most affected country globally in 2018 by the Global Climate Risk Index. With SPEI serving as a valuable tool for monitoring and analysing these impacts. In this study, we would like to know whether nitrogen fertilization could compensate for drought effects on the crop yield of winter wheat by addressing this objective, the study outlines a series of tasks: (1) Analysing Nitrogen Use Efficiency (NUE) over a span of years from 2018 to 2021, (2) quantifying drought intensity through satellite-derived Standardized Precipitation Evapotranspiration Index (SPEI) and Effective Drought Index (EWDI), and (3) examining the impacts of both annual and monthly drought occurrences on yield, followed by an assessment of resulting variations in NUE. We used a new and comprehensive drought index, known as Standardised Precipitation-Evapotranspiration Index (SPEI), to track meteorological drought. This index is derived from the Spanish National Research Council (CSIC) database, covering the period from 2008 to 2021. The data was collected from various winter wheat fields situated in the southern part of Bavaria, specifically in the Freising area, Germany. The results show a strong correlation between NUE and crop yield, making it particularly suitable for assessing drought in moist regions like Germany, while EWDI yields more accurate results in arid regions. This underscores the importance of studying the connection between drought events and nitrogen use efficiency (NUE) when studying the effects of drought on crop yield. SPEI is employed to evaluate the effects of drought on crops and the availability of water for plant growth. In the context of Nitrogen Use Efficiency (NUE), SPEI aids in identifying the relationship between drought and nitrogen utilization efficiency in plants.

1. **Introduction**

Over the past few decades, human-induced actions have caused a rise in the levels of greenhouse gases in the atmosphere (Grosser & Schmalz, 2023). This has led to a global increase in average temperatures and alterations in meteorological factors. These changes in climate have resulted in extreme hydroclimatic events, such as droughts, with significant consequences for water scarcity and arid conditions (Arnone et al., 2020). According to the Global Climate Risk Index, Germany was identified as the third most affected country globally in 2018, especially due to the impacts of heatwaves and droughts (Eckstein et al., 2019). Although the effects of climate change differ across regions, countries like Germany, situated in central and northern Europe with generally mild climatic conditions, have not typically been the primary focus of drought research.

Noor et al. (2022) emphasizes that insufficient rainfall during the initial stages or excessive soil water consumption typically leads to a lack of water during the crucial growth phase of wheat. This shortage is responsible for a reduction in wheat yield, as it results from a deficiency in the soil water reserve. Meanwhile, in numerous parts of the world, an increase in N-fertilizer input was essential to increase crop profit (Manschadi & Soltani, 2021). Therefore, it is speculated that in period of droughts, N fertilization could compensate for the reduction of yield in winter wheat. However, addition to its impact on yield and profit, N fertilization may have important environmental consequences owing to its potential effect on nitrogen leaching and deep drainage to groundwater (Sadras, 2002). This underscores the importance of studying the connection between drought events and nitrogen use efficiency (NUE), as a management and environmental indicator for N fertilization, on the crop yield of winter wheat.

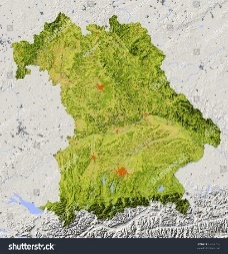
Proper evaluation and tracking of drought conditions are crucial for crop management practices, particularly in significant crops like wheat, involving timely irrigation and intercultural operations. The assessment of drought severity in a region is commonly done through drought indices derived from hydrometeorological or climatic data (Ndayiragije & Li, 2022). Understanding and enhancing the performance of these indices are essential for crop resilience in the face of changing climate patterns and sustainable water resource management. Meteorological drought indices, including the Palmer Drought Severity Index, Standardized Precipitation Index, Standardized Precipitation Evapotranspiration Index (SPEI), and Evaporative Water Demand Index (EWDI), have gained popularity and seamlessly integrated into modern remote sensing methodologies (Wei et al., 2021). The SPEI, a critical measure for assessing drought conditions, adopts a water balance methodology by evaluating the variance between precipitation and potential evapotranspiration to identify wet and dry periods across different time series (Beguería et al., 2014). This time series can be further utilized to analyze spatiotemporal trends in drought severity and its implications for crop yield (Okal et al., 2020). Numerous studies have shown that the SPEI exhibits a more robust correlation with hydrological and ecological parameters compared to alternative drought indices (Beguería et al., 2014).

Models centred on energy and energy-intensive processes such as evapotranspiration, drying, and solar radiation absorption, are fundamental for enhancing our understanding of the dynamics between the energy and water cycles within a given agroecosystem. The technique we are employing, known as EWDI, is constructed based on the land surface temperature and land surface albedo differences with values further factored for the latitude and longitude of a place. The state of water and, consequently, the level of drought stress experienced can be estimated by analysing the Energy-based Water Deficit Index (EWDI), which serves as an indicator of water deficiency (Sur et al., 2015). Since the energy, water, and carbon between the soil surface and the atmosphere are taken in EWDI, it can better reflect on the complex interactions between drought conditions associated with the atmosphere and vegetation. This method has been successfully employed in Korean, Australian and Mongolian regions. The accuracy of EWDI was compared with actual ground measured spatial-temporal distribution of drought and found to be higher than other similar indices (Sur et al., 2019). While EWDI focuses on the energy-water dynamics within ecosystems, SPEI primarily considers precipitation and temperature variations, and both these different approaches are used here complementarily to gain a comprehensive understanding of the extreme conditions faced in Freising.

In this study we would like to know whether nitrogen fertilization could compensate for drought effects in winter wheat yield production? To answer this question, we implemented the series of the following objectives: (1) Analyzing NUE across different years from 208 to 2021, (2) quantifying the drought intensity using satellite derived SPEI and EWDI, (3) investigating the effects of yearly and monthly drought on yield and subsequently NUE variations.

1. **Material and Method**
2. **Ground Measured Data**

The field measurements were carried out using data provided by Field Crops Unit Department of TUM, covering the period from 2008 to 2021. The data was collected from various winter wheat fields situated in the southern part of Bavaria, specifically in the Freising area, Germany. It is important to note that this project did not consider detailed information on farm management practices or the specific wheat varieties used in the designated locations.

A map of land with red squares

Description automatically generated

**Figure 1. Map of The Study Area Situated in The Southern Part of Bavaria, Germany**

In our research, we focused on assessing grain yield and nitrogen fertilization as key variables. To facilitate our analysis, we utilized shapefiles, which were initially pre-processed using QGIS (Quantum Geographic Information System).

The dataset consists of a Shapefile supplemented with extra data achieved by merging field names. This merging process provides us with details regarding the use of nitrogen fertilization and crop yield. Subsequently, we utilize this information to calculate the NUE.

The NUE is providing insight into the efficiency of nitrogen utilization by the crop. Higher NUE values indicate more efficient use of nitrogen inputs, whereas lower values may suggest potential inefficiencies or losses of nitrogen. In a separate subsection, we elaborate on the automation procedure employed in our study. This procedure aimed to streamline and enhance the efficiency of our analyses. Details of the automation process, including specific steps and methodologies, are provided in this dedicated section.

For additional transparency, the PyQGIS script utilized in the automation procedure is included in the Annex. This script serves as a valuable resource for replicating and understanding the automation steps taken in our research, providing a comprehensive overview of the methods applied in our study.

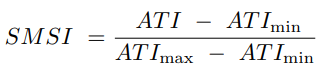
1. **EWDI (The Energy-Based Water Deficit Index)**

EWDI is a unitless metric utilized for evaluating moisture levels, spanning from unlimited positive values, signifying saturated conditions, to unlimited negative values, indicating arid conditions. Moderate Resolution Imaging Spectroradiometer (MODIS), aboard Terra, and Aqua satellites, captures data of the Earth's surface every 1 to 2 days, across 36 spectral bands and the dataset from these is accompanied by numerous valuable data products. EWDI utilizes remote sensing observations of the land surface obtained from MODIS at a spatial resolution of up to 1 km. The analysis was done on Google Earth Engine using the area variable processed earlier in QGIS and the period set from

EWDI is calculated by subtracting the Standalone MODIS-based Evaporative Stress Index (stMOD ESI) from the Soil Moisture Saturation Index (SMSI):



SMSI is derived using the following relation:

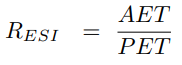


Where ATI denotes the disparity between the diurnal variation in Land Surface Temperature (ΔLST) and Land Surface Albedo (α):



A dataset comprising MOD11A2 images, from which the ‘LST\_Day\_1km’ band is selected, and MCD43A3 images, from which the ‘Albedo\_BSA\_shortwave’ band is selected, is utilized for obtaining Land Surface Temperature (LST) and albedo (α) data, respectively. MOD11A2 Version 6.1 product, offered an average 8-day per-pixel Land Surface Temperature and Emissivity (LST&E) at a 1-kilometer (km) spatial resolution within a 1,200 by 1,200 km (about 745.65 mi) grid. Meanwhile, The MODIS MCD43A3 Version 6.1 Albedo Model dataset, derived from Terra and Aqua MODIS data, provided daily albedo information at a 500-meter (m) resolution, integrating data from 16-day periods with temporal weightage to the ninth day in the interval.

ESI utilizes the ratio of potential evapotranspiration (PET) to actual evapotranspiration (AET), represented as



AET and PET are initially computed using standalone MODIS-based algorithms to address standardized anomalies in the *RESI* ratio, as proposed by Sur et al. (2015). We utilized the MOD16A2GF Version 6.1 Evapotranspiration/Latent Heat Flux (ET/LE) product from MODIS, as the former is an 8-day composite dataset with a pixel resolution of 500 meters (about 1640.42 ft), for computing refined ESI parameter stMOD ESI. The refined ATI i.e., SMSI was recursively estimated in GEE subsequently.

1. **SPEI (Standardized Precipitation Evapotranspiration Index)**

This study uses SPEI, a new and comprehensive drought index proposed by Vicentro et al., to track meteorological drought. The SPEI is calculated based on precipitation (P) value and potential evapotranspiration (PET) value and reflects the basic computation of the water balance in the climate at different time scales. Computation of SPEI is first done by standardizing the differences in P and PET values using log-logistic probability distribution function given by the equation:

Where α = scale parameter, β = shape parameter, y = beginning parameter, and x = mean of series Cumulative Water Balance (CWB).

The monthly WB is obtained from subtracting PET from monthly precipitation data.

**WB = P – PET**

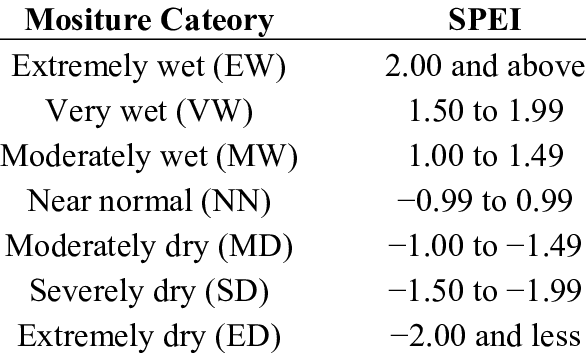
With the log-logistic probability distribution function calculated, SPEI can then be calculated with the formula.

Where, W = for *p ≤ 0.5,* and P is the probability of exceeding a determined WB value.

The constants are C0 = 2.515517, C1 = 0.802853, C2 = 0.010328, d1 = 1.432788, d2 = 0.189269, and d3 = 0.001308 (Beguería et al., 2013).

In this study, SPEI analysis is carried out by collecting data from the SPEI base: Standardised Precipitation-Evapotranspiration Index database, Version 2.9 provided by the Spanish National Research Council (CSIC). All this data was taken from Google Earth Engine data over a period of 10 months, starting from October to July of the following year. The band used were “SPEI\_01\_month” for monthly values of SPEI and “SPEI\_10\_month” for yearly values of SPEI. The SPEI index (**Table 1.)** are used to observe the severity of drought.

**Table 1. SPEI drought indexes**



**Precipitation**

In the research methodology, precipitation data was collected from the Global Measurement Precipitation (GPM-v6) dataset, covering the period from 2008 to 2021. The data, measured in units of millimetres per month, was acquired monthly. Specifically, the 'precipitationCal' band was utilized for the analysis. This dataset provides a comprehensive overview of precipitation patterns over the specified time limit.

**PET**

Potential evapotranspiration data was gathered from the Global Land Data Assimilation System (GLDAS 2-1). Similar to the precipitation data, the potential evapotranspiration data was collected monthly, measured in units of millimetres per month. For this aspect of the study, the 'PotEvap\_tavg' band from the GLDAS 2-1 dataset was employed. This information is crucial for understanding the evaporative demand in the study area, contributing to a comprehensive analysis of the water balance within the specified time limit.

**Temperature**

Temperature data was collected from the Global Land Data Assimilation System (GLDAS), specifically utilizing the "Tair\_f\_inst" band. The temperature data spanned the period from 2007 to 2021. The data was collected on a yearly basis, providing insights into the variations in air temperature over the specified duration. The "Tair\_f\_inst" band was instrumental in capturing instantaneous air temperature measurements, contributing valuable information for the comprehensive analysis of climatic conditions during the study period.

**Correlation test**

Spearman correlation tests were conducted in R to examine the monotonic relationship between EWDI and SPEI values with NUE and Crop Yield variables. This choice was made due to Spearman correlation's robustness against outliers, independence from normal distribution assumptions, and ability to capture monotonic relationships between the variables EWDI and SPEI with NUE and Crop Yield

1. **Result**
2. **Ground Measured Data**

The Nitrogen Use Efficiency (NUE) is a measure that expresses the proportion of applied nitrogen fertilizer that is absorbed and removed by the harvested crop. It is calculated by dividing the amount of nitrogen removed through the crop yield by the amount of nitrogen fertilizer applied. NUE is typically expressed as a percentage. This metric provides insights into the relative utilization or efficiency of the additional nitrogen applied to an agricultural production system within a specific region.

**Table 2. Nitrogen Use Efficiency (NUE) Findings**

|  |  |  |  |
| --- | --- | --- | --- |
| **Year** | **Crop Yield (dt/ha)** | **Average N-Fertilisation** | **NUE %** |
| 2008 | 70,94 | 130,31 | 54% |
| 2009 | 64,14 | 157,58 | 41% |
| 2010 | 62,11 | 162,53 | 38% |
| 2011 | 82,34 | 197,54 | 42% |
| 2012 | 79,45 | 161,33 | 49% |
| 2013 | 89,79 | 150,67 | 60% |
| 2014 | 89,41 | 175,71 | 51% |
| 2015 | 84,75 | 220,00 | 39% |
| 2017 | 71,80 | 205,00 | 35% |
| 2018 | 72,53 | 162,65 | 45% |
| 2019 | 71,90 | 194,00 | 37% |
| 2020 | 81,81 | 135,88 | 60% |
| 2021 | 75,33 | 148,00 | 51% |

We observed that even though the average NUE decreased in the years 2015 and 2017, the crop yield was not appreciably affected. Likewise, from the data, higher NUE did not translate to a higher expected yield. Therefore, to get a clear picture we correlated the NUE and Crop Yield as shown in the figure (Spearman Correlation = 0.51).

A graph with a line and numbers

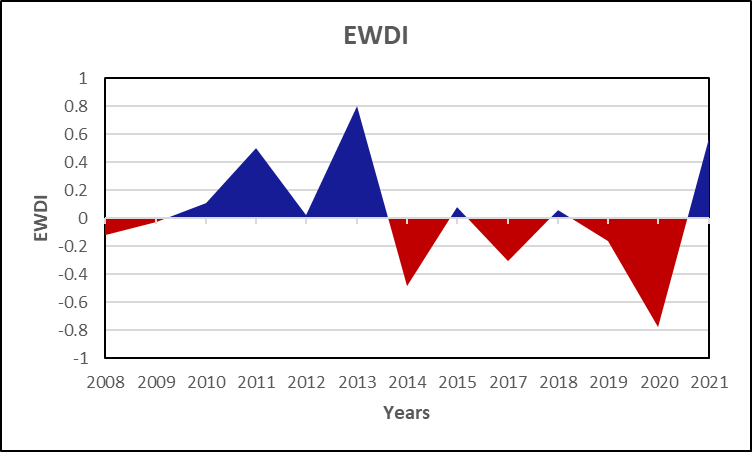
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**Figure 2. Correlation between NUE and Crop Yield**

To elucidate these findings, we conducted a correlation analysis between NUE and Crop Yield, aiming to uncover underlying patterns. The resulting positive correlation coefficient of 0.51, though indicative of some relationship, fell short of expectations considering the direct incorporation of crop yield in the NUE calculation. This discrepancy prompts further investigation into additional contributing factors, such as climatic variables like drought, soil characteristics, or management practices. Considering these complexities, we look for deeper insights from our indices mentioned in the methodology.

1. **EWDI (Energy-Based Water Deficit Index)**

EWDI functions as a drought index by combining information about energy balance and water availability. EWDI here considers the following aspects related to drought, evapotranspiration, land surface temperature and soil moisture content. This provides a more holistic perspective on drought severity compared to indices solely based on water availability data on a monthly then proceeding to convert it to the yearly basis. EWDI offers the ability to monitor drought conditions over large areas efficiently, making it suitable for regional and global-scale assessments. EWDI often provides continuous data, allowing for real-time monitoring of drought development and progression.



**Figure 3. Time Graph of EWDI**

|  |  |
| --- | --- |
| a) Spearman Correlation: 0.2146 | b) Spearman Correlation: 0.1303 |
|  |  |
| c) Spearman Correlation: 0.14283 | d) Spearman Correlation: 0.5390 |
|  |  |
| e) Spearman Correlation: 0.1004 | f) Spearman Correlation: 0.03037 |
|  |  |

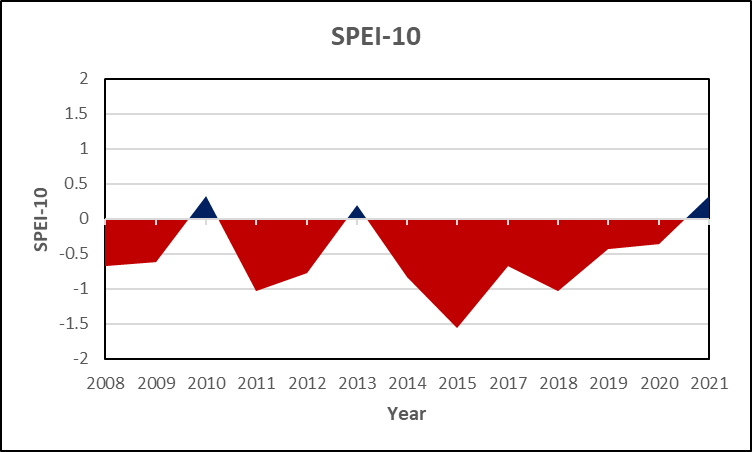
**Figure 4.** **Spearman correlation graph of EWDI, f\_ET and SMSI to NUE and Crop Yield.**

**Table 3. f\_ET, SMSI and EWDI along with Nitrogen Fertilization and Crop Yield**



1. **SPEI (Standardized Precipitation Evapotranspiration Index)**

SPEI combines information on precipitation, evapotranspiration, and temperature to provide an overview the relation among those parameters together with the NUE and drought in the determined study area. The index is adjusted for seasonal and geographical variability, enabling better comparisons between locations.



**Figure 5. Time Graph of SPEI-10 from the period of 2008 to 2021. Taken from GEE with area of interest in Freising, Southern Bavaria, Germany.**

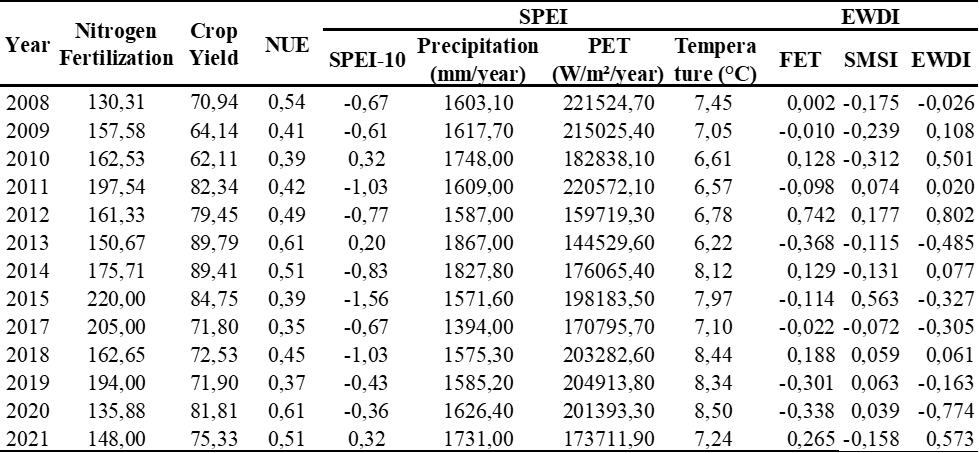
Throughout the period spanning from 2008 to 2021, Germany has consistently experienced recurring negative values of SPEI. However, notable drought events were primarily confined to the years 2011, 2015, and 2018, with no significant drought occurrences observed in the intervening years. Monthly value of SPEI (SPEI-1) can be found in **Annex 1.**

|  |  |
| --- | --- |
| a) Spearman correlation 0.3323653 | b) Spearman correlation -0.249706 |
|  |  |
| c) Spearman correlation 0.5638001 | d) Spearman correlation 0.371286 |
|  |  |
| e) Spearman correlation -0.240330 | f) Spearman correlation -0.385922 |
|  |  |
| g) Spearman correlation 0.028508 | h) Spearman correlation 0.064906 |
|  |  |

**Figure 6.** **Spearman correlation graph of SPEI, Precipitation (P), Potential Evapotranspiration (PET) and Temperature (Temp) to NUE and Crop Yield.**

**S**PEI exhibits a weak positive correlation with NUE, while showing a weak negative correlation with Crop Yield. For precipitation, it exhibits a moderate positive correlation with NUE and a weak positive correlation with Crop yield. For PET, it exhibits a weak negative correlation with NUE and a weak negative correlation with Crop yield. And lastly for Temperature, it exhibits a very weak positive correlation with NUE and Crop Yield

**Table 4. Overview Of Ground Measured Data Along with SPEI and Its Factors (Precipitation, PET, And Temperature) from The Year 2008 To 2021**



The yearly analysis of ground-measured data alongside SPEI data reveals a noteworthy observation. Specifically, in 2015, despite encountering the most severe drought conditions, there was no significant decrease in Crop Yield. Coinciding with this, there was a substantial increase in Nitrogen fertilizer application. This suggests a potential mitigation effect of Nitrogen fertilization on drought impacts.

1. **Discussion**
2. **SPEI**

The SPEI is the intensity of drought at a multi-scalar level, taking account of the precipitation and potential evapotranspiration data together. In the result, we saw a moderate positive correlation between SPEI and NUE which are to be expected with the reason that higher moisture results in enhanced N uptake by wheat plants or reducing amount of N lost (Quemada and Gabriel, 2016; Hamed et al., 2019). In contrast, we saw a mild negative correlation between SPEI and Crop Yield. This could be attributed to farmers increasing the N fertilization rate during drought years, mitigating crop yield losses as reported by Saneoka et al. (2004) & Yang et al. (2011). During the yearly SPEI-10 result from 2008-2021, we saw that Germany did not experience drought except for the year 2011, 2015, and 2018. Which are in line with some of the reports published previously (Hoy et al., 2016; Masante & Vogt, 2018; Reinermann et al., 2019) where drought was observed during these years.

Interestingly in these years, the crop yield is not significantly reduced by the drought, and we also seen an increase in Nitrogen Fertilization during these years. The data suggests that farmers had tried to mitigate the effects of drought by increasing the Nitrogen Fertilization of crops. Indeed, according to the research by Mandic et al. (2015), the increase of N fertilization also resulted in a higher yield. This could be attributed to interactions between Nitrogen and Water eg. N encourages higher transpiration in drought conditions leading to improved plant growth (Araus et al., 2020). While many factors such as soil properties, wind, sunlight and potential pest and diseases may also play a role in crop yield (Adi, Komori, and Kim, 2023).

1. **EWDI:**

* Explaining f\_ET relation to NUE and Crop yield:

**f\_ET vs Crop Yield:** In general, f\_ET and Crop Yield should be negatively correlated. Crop output often declines with increasing f\_ET, which indicates increased water stress. Limited water availability, which impedes crop growth and development, is the cause of this yield drop. However, several factors which might affect how strong this negative link is.

**f\_ET vs. NUE:** The extent of water stress affects the more intricate link between f\_ET and NUE. Plants may enhance their NUE as a compensatory strategy to maximise water use efficiency in the presence of mild water stress. Severe water stress, on the other hand, limits the availability of both water and nitrogen, which inhibits plant growth and nutrient absorption. When water stress reaches excessive levels, this might lead to a negative association between f\_ET and NUE.

* Explaining SMSI relation to NUE and Crop yield:

**SMSI vs. Crop Yield:** Crop yield and SMSI are expected to positively correlate. Plants gain from increased water availability when SMSI rises, suggesting higher soil moisture levels. Water is necessary for several physiological activities, including photosynthesis and nutrient absorption. Better plant growth and development as a result usually increases agricultural production. However, several variables, including crop variety, environment, and farming techniques, might affect how strong this association is, but the insufficient, irregular data might also play a huge part in altering the relations. But in general, there are water needs that vary between crops, and temperature and evapotranspiration rates are two major determinants of water use. Additionally, irrigation practices can play a significant role in supplementing water during dry periods, affecting the relationship between SMSI and crop yield.

**SMSI vs. NUE:** There is an indirect correlation between SMSI and Nitrogen Use Efficiency (NUE), which is frequently mediated through crop production. Greater crop growth is often facilitated by higher SMSI levels, which lessen the energy required by plants to take up nitrogen from the soil. This may result in a somewhat elevated NUE in circumstances with a modest SMSI. Still, even with higher nitrogen utilisation efficiency, extreme water stress circumstances can reduce crop production and NUE. In these circumstances, any gains in NUE may be overshadowed by restrictions on the supply of water, which would lower production overall.

* Explaining EWDI relation to NUE and Crop yield:

**EWDI vs. Crop Yield:** Crop yield and EWDI have a predicted negative relationship, with rising EWDI values indicating deteriorating drought conditions. The increase in the EWDI indicates that there is less water available for plants since actual evapotranspiration is lower than potential rates. This is supported by the decrease in the FET (ratio of Actual Evapotranspiration to Potential Evapotranspiration) and SMSI. Reduced photosynthesis, slowed root growth, and decreased nutrient absorption are just a few of the difficulties that restricted water availability presents to plant growth and development. These factors eventually result in a drop in agricultural production.

**EWDI vs. NUE:** Nitrogen Use Efficiency (NUE) and EWDI also have a complicated connection that depends on how severe the water stress is. When there is a mild drought (low to moderate EWDI values), plants may increase their NUE to maintain sufficient nitrogen absorption and maximise water usage efficiency. Even though there may be modifications in NUE, severe drought conditions (shown by high EWDI values) lead to severely restricted water and nitrogen availability, which hinders plant development and nutrient uptake.

The EWDI is a vital indicator of drought stress as it shows how much water is available to plants. High EWDI values signify lower water availability because of lower Actual Evapotranspiration (AET) relative to Potential Evapotranspiration (PET) and lower Soil Moisture Saturation Index (SMSI). As the drought worsens, expected results show a negative association between EWDI and crop output. High EWDI values cause limited availability to water, which hinders vital physiological functions including photosynthesis and absorption of nutrients. Plant growth and development are thus stunted, which lowers agricultural production.

Overall, from the calculations of EWDI, TUM field experiences a lot of droughts in the year of 2008, 2009, 2014, 2017, 2019, 2020 and maximum drought was in 2019 with value of -0.77. But interestingly crop yield was not affected in these years (Table2).

1. **Conclusion**

The correlation between NUE and drought indices is crucial for mitigating the impact of nitrogen fertilizer when studying the effects of drought on crop yield.

Climate change and weather patterns exert considerable influence on drought levels, with SPEI serving as a valuable tool for monitoring and analysing these impacts. SPEI demonstrates strong correlation with crop yield, making it particularly suitable for assessing drought in moist regions like Germany, while EWDI yields more accurate results in arid regions such as Korea and Australia.

SPEI is employed to evaluate the effects of drought on crops and the availability of water for plant growth. In the context of Nitrogen Use Efficiency (NUE), SPEI aids in identifying the relationship between drought and nitrogen utilization efficiency in plants.

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**ANNEX**

**Annex 1.**

A graph with red and blue lines

Description automatically generated

**Annex 2.**

A graph with red and blue lines

Description automatically generated

**Annex 3. Monthly SPEI-1 data collected from Freising, Southern Bavaria, Germany from October 2007 to July 2021**

1. **PyQGIS Code**

|  |
| --- |
| # Importing necessary libraries  from qgis.core import \*  import pandas as pd  import csv  import processing  import os  import time  # Path to shapefile and Excel file  shapefile\_path = "C:\\Users\\Aman\\Desktop\\local\_RP\\R.P Smart Farming\\merge\_merge\_merge.shp"  excel\_file\_path = f'C:\\Users\\Aman\\Desktop\\local\_RP\\R.P Smart Farming\\alldata\_filtered\_years\_updated\_1.xlsx'  # Loading the shapefile into a QGIS vector layer  layer = QgsVectorLayer(shapefile\_path, "boundaries+f", "ogr")  # Checking if the layer is valid  if not layer.isValid():  print("Invalid shapefile")  # Adding the layer to the QGIS project  QgsProject.instance().addMapLayer(layer)  # Function to select features from the shapefile based on Excel data for a specific year  def ultimate\_function(year):  # Loading Excel data into a QGIS vector layer  xlayer = QgsVectorLayer(f'C:\\Users\\Aman\\Desktop\\local\_RP\\R.P Smart Farming\\{year}.xlsx', 'test', 'ogr')  # Lists to store feature names and expressions  schlag\_names = []  expressions = []  # Iterating through features in the Excel layer  for i in xlayer.getFeatures():  schlag\_names.append(i[1])  expressions.append(f'"Name"=\'{i[1]}\'')  fexpressions = list(set(expressions))  # Combining expressions using OR operator  combined\_expression = ' OR '.join(fexpressions)  layer.selectByExpression(combined\_expression, QgsVectorLayer.SetSelection)  print(fexpressions)  # Creating directory for output shapefiles  directory\_path = f"C:\\Users\\Aman\\Desktop\\local\_RP\\output\_data\\shapefiles\_{year}"  if not os.path.exists(directory\_path):  os.makedirs(directory\_path)  print("Directory '{}' created successfully".format(directory\_path))  else:  print("Directory '{}' already exists".format(directory\_path))  # Output shapefile path  fn = f'C:\\Users\\Aman\\Desktop\\local\_RP\\output\_data\\shapefiles\_{year}\\shapefile\_{year}.shp'  # Writing selected features to a new shapefile  writer = QgsVectorFileWriter.writeAsVectorFormat(layer, fn, 'utf-8', driverName='ESRI Shapefile', onlySelected=True)  selected\_layer = iface.addVectorLayer(fn, '', 'ogr')  del(writer)  # Deleting specified fields from the new shapefile  fieldnames\_to\_delete = ['Jahr','Flaeche', 'LFlaeche']  my\_vectorlayer = iface.activeLayer()  with edit(my\_vectorlayer):  fields\_to\_delete = []  for fieldname\_to\_delete in fieldnames\_to\_delete:  fieldindex\_to\_delete = my\_vectorlayer.fields().indexFromName(fieldname\_to\_delete)  if fieldindex\_to\_delete == -1:  continue  fields\_to\_delete.append(fieldindex\_to\_delete)  my\_vectorlayer.dataProvider().deleteAttributes(fields\_to\_delete)  my\_vectorlayer.updateFields()  # Function to merge shapefile with Excel data for a specific year  def mergeLayer(num):  # Path to vector layer and Excel  vector\_layer\_path = f'C:\\Users\\Aman\\Desktop\\local\_RP\\output\_data\\shapefiles\_{num}\\shapefile\_{num}.shp'  xlsx\_path = f'C:\\Users\\Aman\\Desktop\\local\_RP\\R.P Smart Farming\\{num}.xlsx'  # Directory for output joined layers  joined\_directory\_path = f"C:\\Users\\Aman\\Desktop\\local\_RP\\output\_data\\joined\_layers\_{num}"  if not os.path.exists(joined\_directory\_path):  os.makedirs(joined\_directory\_path)  print(f"Directory '{joined\_directory\_path}' created successfully")  else:  print(f"Directory '{joined\_directory\_path}' already exists")  # Loading vector and Excel layers  vector\_layer = QgsVectorLayer(vector\_layer\_path, 'Vector Layer', 'ogr')  xlsx\_layer = QgsVectorLayer(xlsx\_path, 'Join ', 'ogr')  # Setting join parameters  vector\_field = 'Name'  attribute\_field = 'Schlag'  join\_object = QgsVectorLayerJoinInfo()  join\_object.setJoinFieldName(attribute\_field)  join\_object.setTargetFieldName(vector\_field)  join\_object.setJoinLayerId(xlsx\_layer.id())  join\_object.setUsingMemoryCache(True)  join\_object.setJoinLayer(xlsx\_layer)  # Performing the join operation  vector\_layer.addJoin(join\_object)  vector\_layer.updateFields()  # Renaming fields in the joined layer based on the original Excel file  field\_mapping = {}  for field in xlsx\_layer.fields():  original\_name = field.name()  if vector\_layer.fields().indexFromName(original\_name) != -1:  new\_name = f"{original\_name}\_xlsx"  field\_mapping[original\_name] = new\_name  vector\_layer.renameAttribute(original\_name, new\_name)  vector\_layer.commitChanges()  # Output path for joined layer  joined\_layer\_path = os.path.join(joined\_directory\_path, f'joined\_layer\_{num}.shp')  QgsVectorFileWriter.writeAsVectorFormat(vector\_layer, joined\_layer\_path, 'utf-8', vector\_layer.crs(), 'ESRI Shapefile')  iface.mapCanvas().refresh()  # Adding joined layer to QGIS project  joined\_layer = QgsVectorLayer(joined\_layer\_path, f'Joined Layer {num}', 'ogr')  QgsProject.instance().addMapLayer(joined\_layer)  iface.mapCanvas().refresh()  print('Joined layer imported into QGIS GUI')  print('Done')  # Looping through years and executing functions  for num in range(2008,2022):  excel\_layer = QgsVectorLayer(f'C:\\Users\\Aman\\Desktop\\local\_RP\\R.P Smart Farming\\{num}.xlsx', f'excel\_layer\_{num}', "ogr")  ultimate\_function(num)  time.sleep(10)  mergeLayer(num)  print('End of Script') |

**Annex 4. Google Earth Engine Code:**

|  |
| --- |
| var AOI = rectangle;  Map.addLayer(AOI);  Map.centerObject(AOI);  print('Area of Interest',AOI);    //defining the study period  var startYear = 2007;  var endYear = 2021;  var startMonth = 1;  var endMonth = 12;    var startDate = ee.Date.fromYMD(startYear, startMonth, 1);  var endDate = ee.Date.fromYMD(endYear, endMonth, 31);  var years = ee.List.sequence(startYear, endYear);  var months = ee.List.sequence(1, 12);  var CRS = ee.String('EPSG: 32632') //to avoid later issues while using MODIS data    var f\_ET = ee.ImageCollection("MODIS/061/MOD16A2GF")  .filterBounds(AOI)  .filterDate(startDate, endDate)  .select(['ET', 'PET'])  .map(function(img){return img.divide(10).reproject({crs: CRS, scale: 500}).clip(AOI).copyProperties(img, ['system:time\_start'])}) //needs time\_start to avoid loosing the date of the image collected  .map(function(img){return img.select('ET').divide(img.select('PET')).rename('f\_ET').copyProperties(img, ['system:time\_start']).set('system:id', img.date().format('YYYY-MM-dd'))})    print(f\_ET)  Map.addLayer(f\_ET, {min:0.2, max:0.9}, 'f\_ET\_8-Day') //0.2 & 0.9 are parameters for visualisation    // Create monthly f\_ET.  var monthly\_fET = ee.ImageCollection.fromImages(  years.map(function(y) {  return months.map(function(m) {  var filtered = f\_ET  .filter(ee.Filter.calendarRange(y, y, 'year'))  .filter(ee.Filter.calendarRange(m, m, 'month'))  .mean();  return filtered.set({  'month': m,  'year': y,  'system:id': ee.Date.fromYMD(y,m,1).format('YYYY-MM'),  'system:time\_start': ee.Date.fromYMD(y, m, 1).millis()  }); // to use the parameters later when needed  });  }).flatten() // convert a collection of image collections into a single image collection  );    print(monthly\_fET, 'f\_ET\_Monthly')  Map.addLayer(monthly\_fET, {min:0.2, max:0.9}, 'f\_ET\_Monthly')    // Compute monthly series.  var meanMonthlyfET\_LongTerm = ee.ImageCollection.fromImages(  ee.List.sequence(1, 12).map(function(m) {  var filtered\_mean = monthly\_fET.filter(ee.Filter.eq('month', m)).mean().rename('mean\_LT');  var filtered\_STD = monthly\_fET.filter(ee.Filter.eq('month', m)).reduce(ee.Reducer.stdDev()).rename('stdDev\_LT');  return filtered\_mean.addBands(filtered\_STD).set({'month': m, 'system:id': m});  })  );    print(meanMonthlyfET\_LongTerm)  Map.addLayer(meanMonthlyfET\_LongTerm.select('mean\_LT'), {min:0.2, max:0.9}, 'f\_ET\_Monthly\_LongTerm')    var Anomaly\_fET = monthly\_fET.map(function(image) {  // Get the month of the image.  var year = image.date().get('year');  var month = image.date().get('month');  // Get the corresponding reference image for the month.  var referenceImage = meanMonthlyfET\_LongTerm.filter(  ee.Filter.eq('month', month)).first();  // Check if the images have bands  var hasBands = image.bandNames().size().gt(0);  // Compute the anomaly by subtracting reference image from input image.  var anomalyImage = ee.Algorithms.If(  hasBands,  (image.subtract(referenceImage.select('mean\_LT'))).divide(referenceImage.select('stdDev\_LT')),  image);    return ee.Image(anomalyImage).rename('Anomaly\_fET').set(  'system:time\_start', ee.Date.fromYMD(year, month, 1).millis());  });    print(Anomaly\_fET)  Map.addLayer(Anomaly\_fET, {}, 'fET Anomaly')    print(ui.Chart.image.seriesByRegion(Anomaly\_fET, AOI, ee.Reducer.mean(), 0, 500))    //var ATI = LST & Albedo.  //To get the LST data.  var LST = ee.ImageCollection("MODIS/061/MOD11A2")  .filterBounds(AOI)  .filterDate(startDate, endDate)  .select('LST\_Day\_1km')  .map(function(img){return img.divide(200).reproject({crs: CRS, scale: 500}).clip(AOI).copyProperties(img, ['system:time\_start'])  .set('system:id', img.date().format('YYYY-MM-dd'))});    print(LST)  Map.addLayer(LST,{min:0.2, max:0.9}, 'LST\_8\_days')    //Calculating the Delta\_LST for later use.  var Delta\_LST = ee.ImageCollection("MODIS/061/MOD11A2")  .filterBounds(AOI)  .filterDate(startDate, endDate)  .select(['LST\_Day\_1km','LST\_Night\_1km'])  .map(function(img){return img.divide(200).reproject({crs: CRS, scale: 500}).clip(AOI).copyProperties(img, ['system:time\_start'])  .set('system:id', img.date().format('YYYY-MM-dd'))})  .map(function(img){return img.select('LST\_Day\_1km').subtract(img.select('LST\_Night\_1km')).rename('Delta\_LST').copyProperties(img, ['system:time\_start']).set('system:id', img.date().format('YYYY-MM-dd'))  });    print(Delta\_LST,'Delta LST')  Map.addLayer(Delta\_LST,{min:0.2, max:0.9}, 'Delta\_LST')    //Extract Albedo data.  var Albedo = ee.ImageCollection('MODIS/061/MCD43A3')  .filterBounds(AOI)  .filterDate(startDate,endDate)  .select('Albedo\_BSA\_shortwave')  .map(function(img){return img.divide(1000).reproject({crs: CRS, scale: 500}).clip(AOI).copyProperties(img, ['system:time\_start'])  .set('system:id', img.date().format('YYYY-MM-dd'))});      // Define the filter for the join  var filterTimeEq = ee.Filter.equals({  leftField: 'system:time\_start',  rightField: 'system:time\_start'  });  // Create the inner join object  var innerJoin = ee.Join.inner();  // Apply the inner join  var joinedCollection = innerJoin.apply(Albedo, Delta\_LST, filterTimeEq);  // Define a function to merge the two images into a single image  var mergingFunction = function(image) {  return ee.Image.cat(image.get('primary'), image.get('secondary'))  .copyProperties(image.get('primary'), ["system:id", 'system:time\_start']);  };  // Map the merging function over the joined collection to create a new merged collection  var mergedCollection = ee.ImageCollection(joinedCollection.map(mergingFunction));    print('Merged Collection:', mergedCollection);    // Create monthly LST & Albedo.  var monthly\_mergedCollection = ee.ImageCollection.fromImages(  years.map(function(y) {  return months.map(function(m) {  var filtered = mergedCollection  .filter(ee.Filter.calendarRange(y, y, 'year'))  .filter(ee.Filter.calendarRange(m, m, 'month'))  .mean();  return filtered.set({  'month': m,  'year': y,  'system:id': ee.Date.fromYMD(y,m,1).format('YYYY-MM'),  'system:time\_start': ee.Date.fromYMD(y, m, 1).millis()  });// to use the parameters later when needed.  });  }).flatten() // convert a collection of image collections into a single image collection.  );    print(monthly\_mergedCollection)  Map.addLayer(monthly\_mergedCollection, {min:0.2, max:0.9}, 'monthly\_mergedCollection')    // Compute monthly Delta LST & Albedo series for later analysis.  var LongTerm\_mergedCollection = ee.ImageCollection.fromImages(  ee.List.sequence(1, 12).map(function(m) {  var filtered\_mean = monthly\_mergedCollection.filter(ee.Filter.eq('month', m)).mean().rename(['meanLT\_Albedo','meanLT\_Delta\_LST']);  return filtered\_mean.set({'month': m, 'system:id': m});  })  );    print(LongTerm\_mergedCollection)  Map.addLayer(LongTerm\_mergedCollection, {min:0.2, max:0.9}, 'LongTerm\_mergedCollection');    // To Calculate ATI.  function ATI\_Calc(image){  var ATI = image.expression("(1-Albedo)/LST", {  "Albedo": image.select("Albedo\_BSA\_shortwave"),  "LST": image.select("Delta\_LST")  }).rename("ATI")  return ATI.copyProperties(image, ["system:time\_start"])  }    // Calculating Min & Max ATI for SMSI.  var calculateMinMax = function(image) {  var minMax = image.select('ATI').reduceRegion({  reducer: ee.Reducer.minMax(),  geometry: AOI,  scale: 500,  maxPixels: 1e13  });  return image.set({  'Minimum': minMax.get(minMax.keys().get(1)),  'Maximum': minMax.get(minMax.keys().get(0))  });  };    var ATI\_merged = mergedCollection.map(ATI\_Calc).map(calculateMinMax);  print(ATI\_merged, 'ATI with Min and Max');    //Calculating ATI monthly.  var monthly\_ATI = ee.ImageCollection.fromImages(  years.map(function(y) {  return months.map(function(m) {  var filtered\_ATI = ATI\_merged  .filter(ee.Filter.calendarRange(y, y, 'year'))  .filter(ee.Filter.calendarRange(m, m, 'month'))  .mean();  return filtered\_ATI.set({  'month': m,  'year': y,  'system:id': ee.Date.fromYMD(y,m,1).format('YYYY-MM'),  'system:time\_start': ee.Date.fromYMD(y, m, 1).millis()  }); // to use the parameters later when needed  });  }).flatten() // convert a collection of image collections into a single image collection  );    print(monthly\_ATI,'Monthly ATI')  Map.addLayer(monthly\_ATI, {min:0.2, max:0.9}, 'ATI\_Monthly')    // Compute monthly series.  var meanMonthlyATI\_LT = ee.ImageCollection.fromImages(  ee.List.sequence(1, 12).map(function(m) {  var f\_mean\_ATI = monthly\_ATI.filter(ee.Filter.eq('month', m)).mean().rename('meanATI\_LT');  var f\_SD\_ATI = monthly\_ATI.filter(ee.Filter.eq('month', m)).reduce(ee.Reducer.stdDev()).rename('sdATI\_LT');  return f\_mean\_ATI.addBands(f\_SD\_ATI).set({'month': m, 'system:id': m});  })  );    print(meanMonthlyATI\_LT)  Map.addLayer(meanMonthlyATI\_LT.select('meanATI\_LT'), {min:0.2, max:0.9}, 'ATI Monthly LongTerm')    var Anomaly\_ATI = monthly\_ATI.map(function(image) {  // Get the month of the image.  var year = image.date().get('year');  var month = image.date().get('month');  // Get the corresponding reference image for the month.  var referenceImage = meanMonthlyATI\_LT.filter(  ee.Filter.eq('month', month)).first();  // Check if the images have bands  var hasBands = image.bandNames().size().gt(0);  // Compute the anomaly by subtracting reference image from input image.  var anomalyImage = ee.Algorithms.If(  hasBands,  (image.subtract(referenceImage.select('meanATI\_LT'))).divide(referenceImage.select('sdATI\_LT')),  image);    return ee.Image(anomalyImage).rename('Anomaly\_ATI').set(  'system:time\_start', ee.Date.fromYMD(year, month, 1).millis());  });    print(Anomaly\_ATI)  Map.addLayer(Anomaly\_ATI, {}, 'ATI Anomaly')    print(ui.Chart.image.seriesByRegion(Anomaly\_ATI, AOI, ee.Reducer.mean(), 0, 500))      //SMSI from ATI  function SMSI\_calc(image){  var minMax = image.select('ATI').reduceRegion({  reducer: ee.Reducer.minMax(),  geometry: AOI,  scale: 500,  maxPixels: 1e9  })  var monthly\_SMSI = image.expression("(ATI-Minimum)/(Maximum-Minimum)", {  "Minimum": ee.Number(minMax.get(minMax.keys().get(1))),  "Maximum": ee.Number(minMax.get(minMax.keys().get(0))),  "ATI": image.select("ATI")  }).rename("monthly\_SMSI")  return monthly\_SMSI.copyProperties(image, ["system:time\_start", 'year', 'month'])  }    var monthly\_SMSI = monthly\_ATI.map(SMSI\_calc);  print(monthly\_SMSI, 'monthly\_SMSI');  Map.addLayer(monthly\_SMSI, {min:0.2, max:0.9}, 'monthly\_SMSI')      // Compute monthly series.  var meanMonthlySMSI\_LongTerm = ee.ImageCollection.fromImages(  ee.List.sequence(1, 12).map(function(m) {  var filteredSMSI\_mean = monthly\_SMSI.filter(ee.Filter.eq('month', m)).mean().rename('meanSMSI\_LT');  var filteredSMSI\_SD = monthly\_SMSI.filter(ee.Filter.eq('month', m)).reduce(ee.Reducer.stdDev()).rename('sDSMSI\_LT');  return filteredSMSI\_mean.addBands(filteredSMSI\_SD).set({'month': m, 'system:id': m});  })  );    print(meanMonthlySMSI\_LongTerm)  Map.addLayer(meanMonthlySMSI\_LongTerm.select('meanSMSI\_LT'), {min:0.2, max:0.9}, 'SMSI Monthly LongTerm')    var Anomaly\_SMSI = monthly\_SMSI.map(function(image) {  // Get the month of the image.  var year = image.date().get('year');  var month = image.date().get('month');  // Get the corresponding reference image for the month.  var referenceImage = meanMonthlySMSI\_LongTerm.filter(  ee.Filter.eq('month', month)).first();  // Check if the images have bands  var hasBands = image.bandNames().size().gt(0);  // Compute the anomaly by subtracting reference image from input image.  var anomalyImage = ee.Algorithms.If(  hasBands,  (image.subtract(referenceImage.select('meanSMSI\_LT'))).divide(referenceImage.select('sDSMSI\_LT')),  image);    return ee.Image(anomalyImage).rename('Anomaly\_SMSI').set(  'system:time\_start', ee.Date.fromYMD(year, month, 1).millis());  });    print(Anomaly\_SMSI)  Map.addLayer(Anomaly\_SMSI, {}, 'SMSI Anomaly')    print(ui.Chart.image.seriesByRegion(Anomaly\_SMSI, AOI, ee.Reducer.mean(), 0, 500))    // Define the filter for joining fET and SMSI  var filterTimeEq = ee.Filter.equals({  leftField: 'system:time\_start',  rightField: 'system:time\_start'  });  // Create the inner join object  var innerJoin = ee.Join.inner();  // Apply the inner join  var joinedCollection = innerJoin.apply(Anomaly\_fET, Anomaly\_SMSI, filterTimeEq);  // Define a function to merge the two images into a single image  var mergingFunction = function(image) {  return ee.Image.cat(image.get('primary'), image.get('secondary'))  .copyProperties(image.get('primary'), ["system:id", 'system:time\_start']);  };  // Map the merging function over the joined collection to create a new merged collection  var merged\_fET\_SMSI = ee.ImageCollection(joinedCollection.map(mergingFunction));    print('Merged Anomaly Data:', merged\_fET\_SMSI);      //Calculating EWDI  function calc\_EWDI(input) {  var EWDI = input.select('Anomaly\_fET').subtract(input.select('Anomaly\_SMSI')).rename('EWDI');  return EWDI.copyProperties(input, ["system:time\_start", 'year', 'month']);  }    var Anomaly\_EWDI = merged\_fET\_SMSI.map(calc\_EWDI);  print(Anomaly\_EWDI, 'Anomaly\_EWDI');  Map.addLayer(Anomaly\_EWDI, {min:0.2, max:0.9}, 'Anomaly\_EWDI');    print(ui.Chart.image.seriesByRegion(Anomaly\_EWDI, AOI, ee.Reducer.mean(), 0, 500)) |