Comprehensive Assessment of Drought Impact on Crop Yields Across Iowa Over Two Decades (2000-2022)

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Abstract

Corn and soybeans are pivotal crops in the U.S. agricultural landscape, providing essential vitamins and oils. These two crops dominate approximately 90% of crop production in Iowa. However, their yields are significantly impacted by recurrent drought conditions. A prolonged deficiency in soil moisture characterizes agricultural drought due to sustained precipitation shortfalls. This study aims to quantify widely utilized drought indicators and ascertain their relationships with corn and soybean yields from 2000 to 2022 to identify each crop's most reliable drought indices. The analysis encompasses meteorological and satellite-derived indices alongside crop yield data from the U.S. Department of Agriculture's National Agricultural Statistics Service (NASS). Indices evaluated in this study include the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Palmer Drought Severity Index (PDSI), Evaporative Demand Drought Index (EDDI), Crop Moisture Index (CMI), and Normalized Difference Vegetation Index (NDVI). Our results demonstrate a positive correlation between soybean yields and long-term moisture indices such as SPI-6, SPI-12, SPEI-6, and SPEI-12, indicating these indices' potential utility in forecasting soybean productivity. Conversely, corn yields exhibit fewer regular patterns and are negatively correlated with EDDI, with higher EDDI values coinciding with reduced corn yields, reflecting heightened drought sensitivity. The study finds that soybeans exhibit better resilience to longer-term moisture indicators, whereas corn yields are more adversely affected by drought conditions. The Palmer Drought Severity Index (PDSI) shows a stronger correlation with soybean yields than with corn yields. The findings indicate that corn is generally more susceptible to drought than soybeans in the study region. These insights can inform decision-making for drought relief efforts, farm management strategies, and grain market planning, enabling stakeholders to address potential drought conditions proactively.

Keywords: agricultural drought indicators, SPI, SPEI, NDVI, PDSI, corn yield, soybean yield.

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1. Introduction

Food production is a critical component of food security, directly influencing the availability of essential resources for sustaining life. Nevertheless, food security is multifaceted, encompassing production, availability, access, use, and stability over time (Capone et al., 2014). Many factors, including temperature and precipitation, influence agricultural productivity. These factors affect the development and health of crops, the yearly crop yields, and the cropping system's long-term productivity (Howden et al., 2007; Liang et al., 2017; Ray et al., 2018). Climate change is expected to increase climatic extremes and harm agricultural production (Gornall et al., 2010; Vogel et al., 2019; Alabbad et al., 2023). Previous studies focused on the influence of climate change on agriculture at various geographical levels (Kang et al., 2009; Olesen et al., 2011; Parry et al., 2004). However, these studies did not specifically investigate the climatic extremes, like floods, droughts, etc., with crop production, which could be used to take adaptive measures to enhance cropping methods and mitigate the adverse effects on crop yields.

Drought, a complex natural phenomenon, significantly affects global environmental, societal, and economic domains and poses challenges to sustainable agriculture (Islam et al., 2022; Yesilkoy et al., 2023), particularly in areas dependent on rain-fed systems such as Iowa (Haile et al., 2020; Islam et al., 2024; Savelli et al., 2022; Sen, 2015). Forecasted climatic changes encompass heightened occurrences of extreme weather events, such as drought and floods (Yildirim et al., 2024), which would impact all facets of life, including water supplies, the health and financial circumstances of the population, and crop production (Field, 2012; Raymond et al., 2020; Sivakumar & Stefanski, 2011; Cikmaz et al., 2023). Consequently, it becomes imperative to understand and address these phenomena thoroughly.

Understanding extreme weather events such as flooding and droughts is crucial, given their profound impacts on human life, infrastructure, and properties (Mount et al., 2019). These events can cause extensive damage, disrupting transportation networks (Alabbad et al., 2024), overwhelming drainage systems, and compromising buildings' structural integrity, necessitating costly repairs, and posing significant risks to human safety. Adequate comprehension and communication of these risks are paramount, enabling communities and policymakers to adopt initiative-taking measures (Sermet and Demir, 2022). Utilizing novel data-driven models (Li and Demir, 2022) and decision support systems enhances our ability to predict, monitor, and assess the extent of these events. These systems integrate real-time data, advanced analytics (Sit et al., 2021a; Ramirez et al., 2022), and machine learning (Sit et al., 2021b) to provide accurate, timely information, aiding in preparedness, response, and recovery efforts. By leveraging these technologies, we can develop more resilient infrastructure, foster informed decision-making, and ensure swift, coordinated actions to mitigate the adverse effects of extreme weather, safeguarding both lives and properties.

Furthermore, research by Mukherjee et al. (2018) and Mishra et al. (2021) indicates that anthropogenic activities and climate change have exacerbated the unpredictability and severity of drought events. Droughts can permanently damage precious and sensitive agroecosystems, lead to extensive crop loss, and increase the occurrence of pests and diseases, which in turn diminishes agricultural productivity (Mahdi et al., 2015; Subedi et al., 2023; Tadele, 2017). For instance, the flash drought in the U.S. Central Great Plains in 2012, the most severe drought since 1930, resulted in agricultural losses of $20 billion (Fuchs et al., 2012; Hoell et al., 2020; Hoerling et al., 2014).

Climate change has increased the frequency and intensity of extreme weather, including droughts and floods (Yildirim et al., 2022), thereby imposing significant stress on agricultural systems (Altieri et al., 2015; Cogato et al., 2019; Handmer et al., 2012). Iowa is a key contributor to the U.S. production of corn and soybeans, crops crucial to national economic stability and the global food supply chain (Grassini et al., 2015). The state's agriculture is highly susceptible to climate variability due to its reliance on specific climatic conditions, soil quality, and water availability (Kukal & Irmak, 2018; Tanir et al., 2024).

Drought poses multiple threats, impacting soil moisture levels and reducing crop productivity, leading to economic losses and heightened food insecurity. Iowa has experienced significant economic repercussions from the drought, particularly in the agriculture sector, which has been severely affected during such periods. Drought-related economic losses to Iowa were substantial between 1989 and 2022; crop loss insurance claims alone were over $5.3 billion (Beach et al., 2010; Maisashvili et al., 2023). Research shows that droughts have a significant financial impact on farmers due to reduced agricultural productivity and increased costs associated with irrigation (Foster et al., 2015; Kuwayama et al., 2019; Lu et al., 2020).

Droughts have resulted in substantial economic losses within the broader context of the impact of droughts across the United States. For example, there were significant financial losses in 2012 due to a severe drought. Droughts included the overall cost of U.S. billion-dollar disaster occurrences that year, almost $130.9 billion after inflation (Smith, 2020). This statistic emphasizes the high stakes in drought management and the need for efficient drought preparation and response plans. According to Jin et al. (2017) and Zhang et al. (2015), the severe drought of 2012, which adversely affected the production of corn and soybeans, served as evidence of the significant negative impact that drought, a phenomenon linked to global climate change, has had on agricultural output.

This underlines the need for detailed analyses of drought impacts within agricultural systems to enhance resilience and sustainability. Most of the studies on Iowa have yet to explore drought's effects on agricultural production within the climate change framework. As a result, it is imperative to measure the extent of the drought's impact on agricultural yields in Iowa using a drought index that incorporates temperature and rainfall as critical factors in computing potential evapotranspiration. Implementing such a strategy will help alleviate the impacts of drought and establish a sustainable farming system to optimize agricultural output.

Various drought indices have been developed using multiple types of environmental data, including precipitation, temperature, and soil moisture (Baydaroglu et al., 2024). The Palmer Drought Severity Index (PDSI) (Palmer, 1965), the Standardized Precipitation Index (SPI) (McKee et al., 1993), and the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010) are the primary drought indicators commonly used all over the world. The PDSI analyzes water balance to evaluate drought over a specific timeframe, which restricts its usefulness in assessing meteorological and agricultural drought (Palmer, 1965). In contrast, SPI primarily employs the precipitation variable to determine drought over several periods.

Additionally, it allows for selecting a specific timescale for meteorological, agricultural, and hydrological purposes (Laimighofer & Laaha, 2022; McKee et al., 1993). When looking at drought conditions over time, the Standardized Precipitation-Evapotranspiration Index (SPEI) is better than the Standardized Precipitation Index (SPI) and the Palmer Drought Severity Index (PDSI) because it uses both precipitation and temperature data (Ma et al., 2014; Vicente-Serrano et al., 2010). Studies have used the Standardized Precipitation Evapotranspiration Index (SPEI) to measure the effects of drought on crops on a global scale (Potop et al., 2012; Ribeiro et al., 2019; Tian et al., 2019). Hence, the Standardized Precipitation Evapotranspiration Index (SPEI) at time delays ranging from 1 to 12 months, along with SPI and PDSI, were chosen to assess drought.

In addition to these three commonly used indices, there is also one called EDDI, which was developed by the National Oceanic and Atmospheric Administration (NOAA) and it was a part of NOAA's "Operationalizing an Evaporative Demand Drought Index (EDDI) service for drought monitoring and early warning," The agency is transferring technology. EDDI does not predict droughts but suggests the possibility of droughts in the near future. EDDI does not directly reflect actual evapotranspiration, but the surface's moisture content significantly impacts the measurements (Hobbins et al., 2016; McEvoy et al., 2016). The normalized difference vegetation index (NDVI) (KRIEGLER, 1969) and the crop moisture index (CMI) (Juhasz & Kornfield, 1978) were also looked at in this research to find the one that fits crop yield in Iowa.

This study examined the impact of drought on corn and soybean yields, the two major cultivated crops in Iowa for the period 2000–2022. In this research, different drought indicators were used, including the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Palmer drought severity index (PDSI), evaporative demand drought index (EDDI), crop moisture index (CMI), and normalized difference vegetation index (NDVI). The data sets used to quantify the indices are temperature, soil moisture, rainfall and evapotranspiration measurements. The key objective of this research is to examine the correlation between several drought indices and the crop yields of corn and soybeans in Iowa during 2000-2022. It aims to analyze these links to offer insights that might guide future agricultural practices and policies, enhancing the resilience of the agriculture industry in Iowa.

2. Materials and Methods

The study covers the state of Iowa and integrates atmospheric and spatial data in the analysis. Quantitative approaches, including statistical analyses and GIS tools, were used to analyze the datasets in this research. These methodologies enabled a comprehensive examination of numerical data and geographical patterns pertinent to the study.

2.1. Study Area

This study used 126 meteorological stations in Iowa to monitor atmospheric variables (Figure 1). Those stations were selected based on data availability and consistency. Each station captures atmospheric parameters, including rainfall, temperature, humidity, evaporation, and transmission. The National Agricultural Service (NASS) of the U.S. Department of Agriculture (USDA) produces land cover statistics illustrating the geographical distribution of crops throughout the whole United States (Boryan et al., 2011). These data are spatially explicit, raster-based products where each pixel is categorized based on land-use classification, specifically identifying crop or land cover categories. According to ground truth data obtained by the USDA, the accuracy of the CDL layer exceeds 80% for primary crop types such as corn and soybeans (Boryan et al., 2011; Johnson et al., 2010).

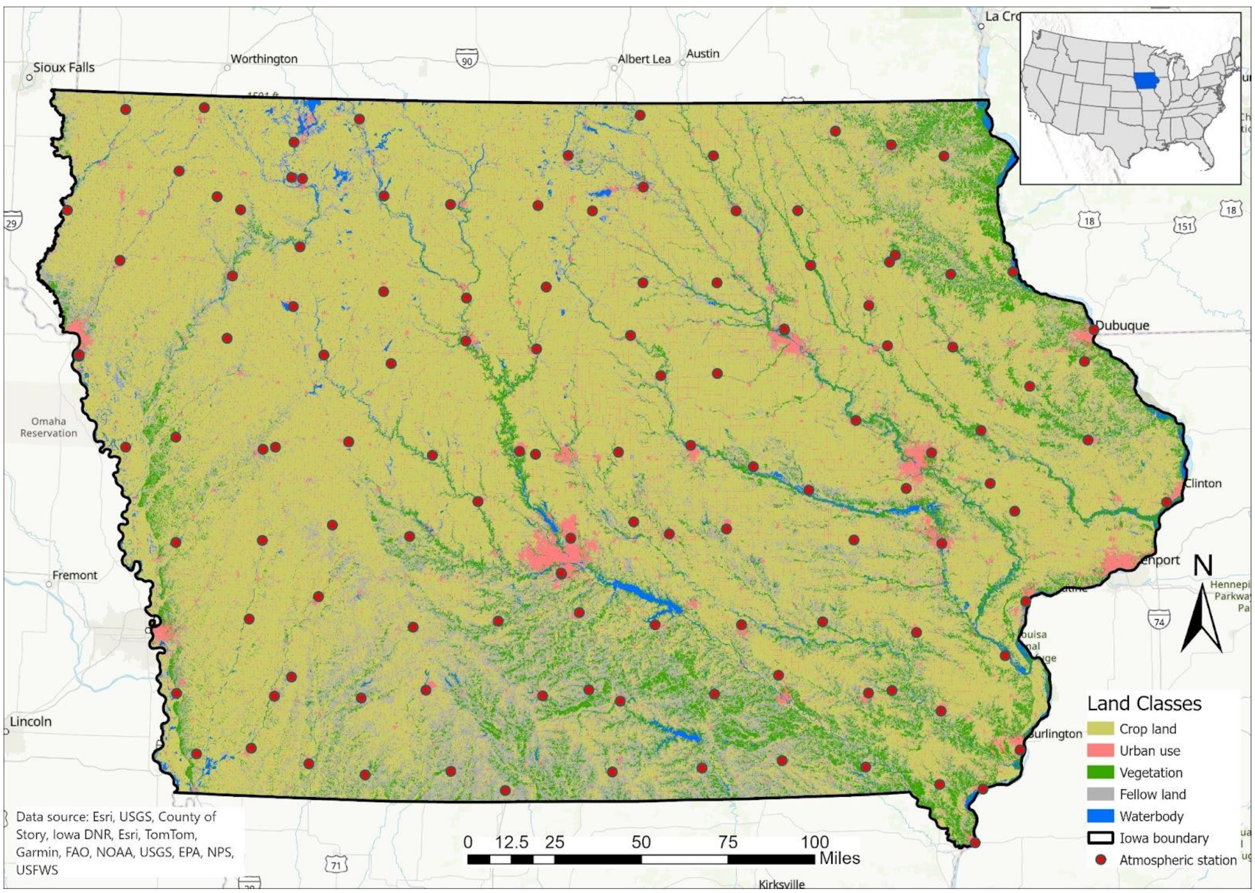

Figure 1: Study area map with land classification and meteorological station location.

Iowa is an agriculturally dominant region in the U.S. Its economy relies heavily on agriculture since almost 85% of its land is agricultural (Bell, 2010). The state is a prominent producer of corn, soybeans, pigs, eggs, and other commodities (Maulsby, 2020). Iowa's environmental landscape is characterized by its flat geography, with elevations varying from 146 meters above sea level in the state's southern section to 509 meters in the northern area (Islam et al., 2024). The state experiences a continental climate, with hot summers and cold winters significantly influencing its agricultural patterns. Iowa's soil is primarily composed of fertile loess, which is ideal for farming due to its excellent drainage and nutrient-rich properties. Many crucial river systems, including the Missouri and Mississippi Rivers, supply the state and are often the main cause of flooding (Yesilkoy et al., 2024). The Missouri River demarcates the western boundary of the state, while the Mississippi River serves as the eastern border. Furthermore, the state includes several smaller rivers, streams, and enormous lakes. All these rivers and streams make the land futile and suitable for crop cultivation.

2.2. Crop Yields

Despite receiving a considerable amount of rainfall annually, Iowa is nonetheless vulnerable to drought, which leads to agricultural failures, water scarcity, and economic losses (Li et al., 2019). According to Li et al. (2019), the recent severe droughts in Iowa, most notably in 2012 and 2021, have seriously harmed livestock and agricultural yields (Yildirim and Demir, 2022). The Midwest of the USA is predicted to experience increasingly frequent and severe droughts due to climate change, emphasizing the need for valuable methods for determining and controlling drought conditions (Holman & Knox, 2023). Due to their suitability and favorable soil conditions, corn and soybeans are the primary crops cultivated in Iowa, constituting almost 90% of the state's total agricultural land (USDA, 2022). The Quick Stats 2.0 website is a detailed tool enabling users to obtain agricultural statistics released by the USDA's NASS (USDA, 2023).

2.2.1. Estimation of Standardized Residual Yield Series (SRYS)

The USDA quantifies agricultural production in bushels per acre using field surveys, farmer reports, remote sensing, and statistical modeling. The estimations are derived from the real-time agricultural yield in the fields rather than the quantity of crops sold in the market. The farm yield data consists of annual regional measurements of corn and soybeans during the research period from 2000 to 2022. Due to improved agricultural methods and the adoption of modern and new technologies, crop output is increasing every year. The linear regression approach was employed to detrend and eliminate the technological/linear trend in the yield. The residual of the yield equation indicates the residual impacts of the weather on the yield (Liu et al., 2018). The Eq. 1 of SRYS is the following:

$$SRYS = \frac{y_i - \mu}{\sigma} \quad \text{Eq. 1}$$

Here, y_i represents the residual of the detrended yield, μ is for the average of the yield residuals, and σ is for the standard deviation. Figure 2 illustrates the corn, and soybean yields after omitting the trend.

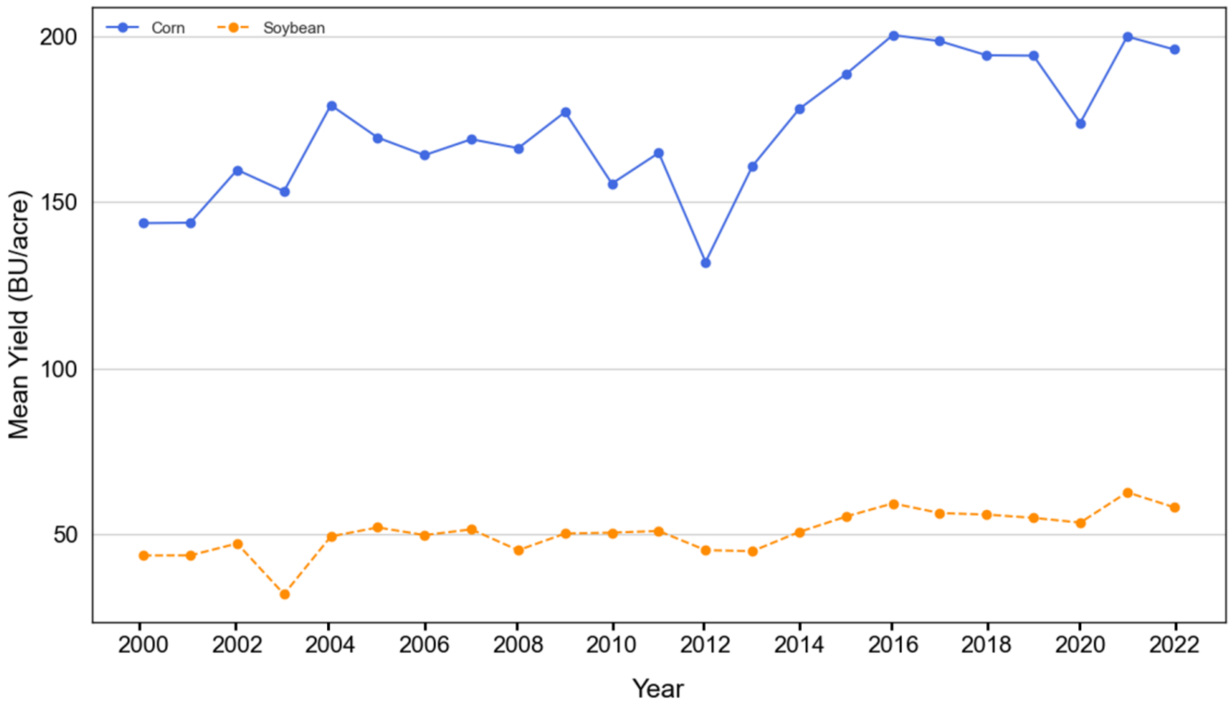

Figure 2: Mean yearly corn and soybean yields in Iowa between 2000 and 2022.

2.3. Drought Indices

2.3.1. The Standardized Precipitation Index (SPI)

SPI quantifies precipitation deficits or surpluses across various time scales. The Standardized Precipitation Index (SPI) is a meteorological indicator for estimating drought quantification across multiple periods, such as 1, 2, 3, 6, 12, and 24 months (McKee et al., 1993). The SPI values typically range from -2.0 to +2.0, where negative values indicate drought conditions and positive values indicate wet conditions. Values near zero suggest average precipitation or mild drought (McKee et al., 1993). This study used meteorological station-based precipitation data obtained from the Iowa Mesonet website to estimate the different time series of the SPI index.

2.3.2. The Standardized Precipitation Evapotranspiration Index (SPEI)

SPEI combines precipitation and potential evapotranspiration (PET) to better account for the effects of temperature on drought assessments. The Standardized Precipitation-Evapotranspiration Index (SPEI) combines precipitation (Pi) and potential evapotranspiration (PETi) data to compute drought conditions. Pi and PETi were utilized to calculate the monthly water balance, represented as Di in the Eq. 2:

$$D_i = P_i - PET_i \qquad \text{Eq. 2}$$

After computing the value of Di at each station, the results were then processed using the SPEI R package to determine the SPEI at various time intervals. Di was fitted using the logarithmic distribution function f(x) in Eq. 3. The SPEIs were derived from numerous time series, including SPEI-1, SPEI-3, SPEI-6, and SPEI-12, using Eq. 4

$$f(x) = \left[1 + \left(\frac{a}{x-\gamma}\right)^{\beta}\right]^{-1} \qquad \text{Eq. 3}$$

Here, a, β, and γ represent the scale, shape of the graph, and the origin parameters, respectively.

$$SPEI = W - \frac{c_0+c_1W+c_2W^2}{1+d_1W+d_2W^2+d_3W^3} \qquad W = \sqrt{-2\ln(P)} \qquad \text{Eq. 4}$$

P = 1-f(x) when P < 0.5; P = 1-P, and the SPEI's sign is inverted when P > 0.5. The values of the constants are d1 = 1.432788, d2 = 0.189269, d3 = 0.001308, c0 = 2.515517, c1 = 0.802853, c2 = 0.010328 c3 = 0.010328. SPEI values also range from -2.0 to +2.0, with negative values indicating drought and positive values indicating wet conditions. The SPEI time series displays positive and negative values corresponding to wet and dry periods. The drought state was determined using a threshold of -1 (SPEI ≤ -1).

2.3.3. Palmer Drought Severity Index (PDSI)

PDSI aims to measure the duration and intensity of long-term droughts using local temperature and moisture data. The index estimates the amount of water stored in the soil using an equation that considers precipitation and the soil's water balance. The anomaly index (z-index) was calculated using cumulative monthly precipitation data. The z-index was determined each month by calculating the difference between the climatically suitable for existing conditions (CAFEC) and actual precipitation. The z-index was incrementally computed using a recursive method. Its value ranges from -4.0 (extreme drought) to +4.0 (extremely moist conditions), making it helpful in tracking prolonged drought or wet spells. The following Eq. 5 and Eq. 6 are used to quantify the PDSI.

$$PDSI = 0.897PDSI_{i-1} + \frac{1}{3}Z_i \qquad \text{Eq. 5}$$

$$Z_i = K_i d_i \qquad \text{Eq. 6}$$

Where i is the dry spell of a specific month, di represents the difference between the original rainfall and the CAFEC one, and Ki is the factor of weight. The primary factors utilized in the PDSI are the air temperature, rainfall, and the Thornthwaite method-based potential evapotranspiration (PET) described by Thornthwaite (1948). monthly observations from 126 meteorological stations were used to calculate the PDSI values.

2.3.4. Evaporative Demand Drought Index (EDDI)

EDDI measures the atmospheric potential to evaporate water, calculated like the SPI and SPEI, which range widely around zero, with higher values indicating higher evaporative demand and potential drought conditions. The viability of applying the two-variable Gamma distribution, specifically for SPI, may be limited when the application area is extensive due to the dependence on parameter-based probability distribution types (Heim Jr et al., 2023). The probability of exceeding the set period, E_o, denoted as P (E_{oi}), is calculated using the following Eq. 7:

$$P(E_{oi}) = \frac{i-0.33}{n+0.33} \qquad \text{Eq. 7}$$

Where *n* represents the total number of years of observations, i is the rank in the previous E_o time series for that specific time duration, and $P(E_{oi})$ represents the probability of exceedance. Here, the mean value of evapotranspiration is applied to that. EDDI index is calculated (Eq. 8) by the inverse version of the normal distribution function as below:

$$EDDI = W - \frac{c_0+c_1W+c_2W^2}{1+d_1W+d_2W^2+d_3W^3} \qquad \text{Eq. 8}$$

Where, c0 = 2.515517, c1 = 0.802853, c2 = 0.010328, c3 = 0.010328, d1 = 1.4328, d2 = 0.1893, and d3 = 0.00131. An EDDI of 0 on any day of the year during a specific period has a median temperature value of 0. Negative Evaporative Demand Drought Index (EDDI) states have more moisture, whereas positive EDDI states have less moisture, resulting in dry circumstances. Thus, the EDDI value rises with drought severity. EDDI variability depends on the length of data collection. For n = 30, values vary from -2 to +2.

2.3.5. Crop Moisture Index (CMI)

CMI is particularly useful in agricultural settings, as it assesses short-term crop moisture conditions and is sensitive to weekly changes. The Crop Moisture Index (CMI) assesses weekly crop conditions using hydrological parameters. Palmer (1968) derived it from PDSI calculating algorithms. CMI value ranges from -3.0 (dry conditions harmful to crops) to +3.0 (excessively wet conditions).

2.3.6. Normalized Difference Vegetation Index (NDVI)

The NDVI utilizes satellite imagery to assess vegetation health by measuring the difference and sum of near-infrared (NIR) and red light (R) reflected by vegetation (Rouse Jr et al., 1974). The two types of MODIS data used were MOD13Q1 and MOD11A1. They were put through five steps, one after the other: (a) mosaicking, (b) projecting the tiles, (c) raster clipping based on the study area using ArcGIS, (d) resampling based on the other raster file to make sure the analysis would work, and finally (e) masking. NDVI is computed using the following Eq. 9:

$$NDVI = \frac{NIR - R}{NIR + R} \quad \text{Eq. 9}$$

Its value ranges from -1.0 to +1.0, where higher values (closer to +1.0) indicate healthier and denser green vegetation, useful for monitoring overall vegetation health, detecting changes in land cover, and estimating biomass. The details of the drought indices are summarized in Table 1:

Table 1: Details of drought indices with their required data and references.

Name of the Drought Index		**Required Data**	**Data Source**	**Reference**
Different SPI time scales	SPI-1	Monthly precipitation data	Iowa Mesonet website (https://mesonet.agron.iastate.edu/rainfall) and climate data centers (NOAA	(McKee et al., 1993)
	SPI-3			
	SPI-6			
	SPI-12			
Different SPEI time scales	SPEI-1	Monthly precipitation and temperature data	Iowa Mesonet website (https://mesonet.agron.iastate.edu) and climate data centers (NOAA)	(Vicente-Serrano et al., 2010)
	SPEI-3			
	SPEI-6			
	SPEI-12			
PDSI		Monthly precipitation and temperature data, soil water holding capacity	Iowa Mesonet website (https://mesonet.agron.iastate.edu) and climate data centers (NOAA)	(Palmer, 1965)
EDDI		Temperature, relative humidity, wind speed, and solar radiation data	Iowa Mesonet website (https://mesonet.agron.iastate.edu) and climate data centers (NOAA)	(Hobbins et al., 2016)
CMI		Weekly precipitation and temperature data	Iowa Mesonet website (https://mesonet.agron.iastate.edu) and climate data centers (NOAA)	(Palmer, 1968)
NDVI		Satellite imagery data (visible and near-infrared light)	Satellite data providers (NASA's MODIS)	(Rouse Jr et al., 1974)

2.4. Quantifying Correlation Analysis

The non-parametric Spearman's rho correlation coefficient was used to analyze the effects of all drought indices on corn and soybean yields, with a significance threshold of $p < .05$ (95%) for each.

3. Results and Discussion

Figure 3 shows the yearly correlation coefficients between corn yield and drought indicators. It demonstrates that shorter-term indices like SPI-1 and SPEI-1 exhibit higher correlation swings, suggesting corn production responds faster to precipitation variability. Longer-term indicators like SPI-12 and SPEI-12 show the cumulative impacts of extended moisture conditions on corn production. Sharp peaks and troughs across numerous indexes are evident in 2005, 2012, and 2018. These years also featured unfavorable weather, reinforcing the links between drought and productivity (Fellman, 2023) and illustrating how severe and ongoing droughts affect agricultural productivity. The 2012 negative correlation in most indices coincided with a severe drought in major corn-producing regions.

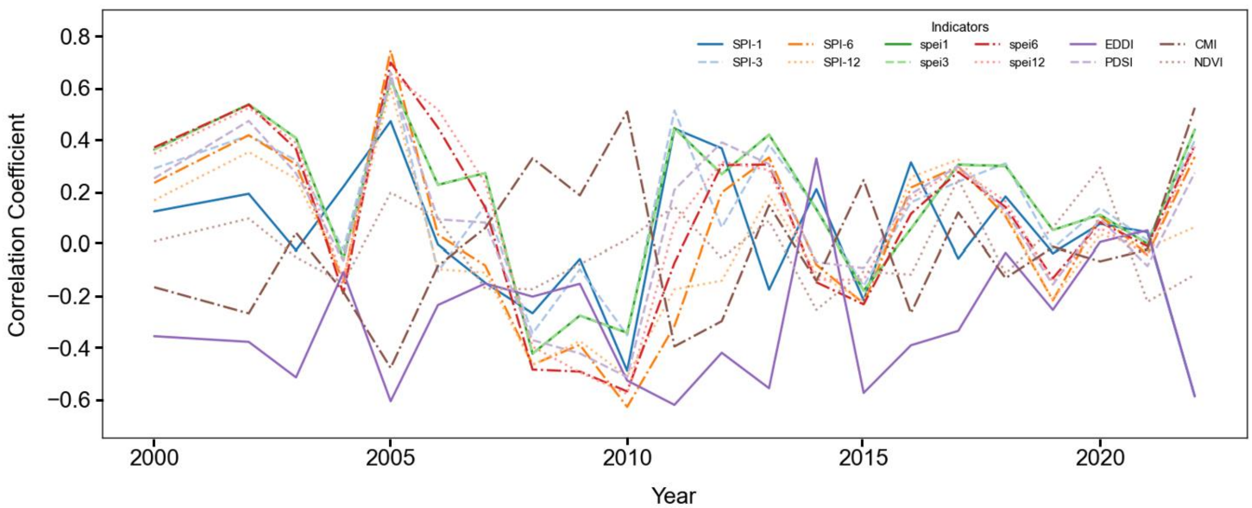

Figure 3: Annual correlation of corn yield with different drought indices.

Conversely, 2004 and 2010 had higher correlations for EDDI and PDSI. Higher correlations between drought indices and productivity suggest that these indices describe the conditions better than other low correlations. The variability in the data is sometimes different, which shows how complicated the relationship is between climate variables and agricultural productivity. It also demonstrates the importance of using more than one drought index in planning farms and managing risks to help mitigate production loss due to short-term and long-term droughts. Drought indices provide a comprehensive understanding of how drought impacts agricultural production by analyzing various aspects of drought, such as soil moisture, plant health, and precipitation deficits.

Previous studies have typically considered only a few drought indices, and research is scarce in Iowa that correlates crop yields with all the common drought indices in this region. This research addresses this gap by identifying which drought indices correlate most with corn and soybean yields in Iowa. The effectiveness of each index depends on the type of drought being tracked, the agricultural context, and the local climate. Some indices are more adept at detecting short-term droughts, while others are better suited for assessing long-term droughts. By evaluating the full range of standard drought indices, this study aims to provide a more complete picture of drought impacts on crop yields in Iowa.

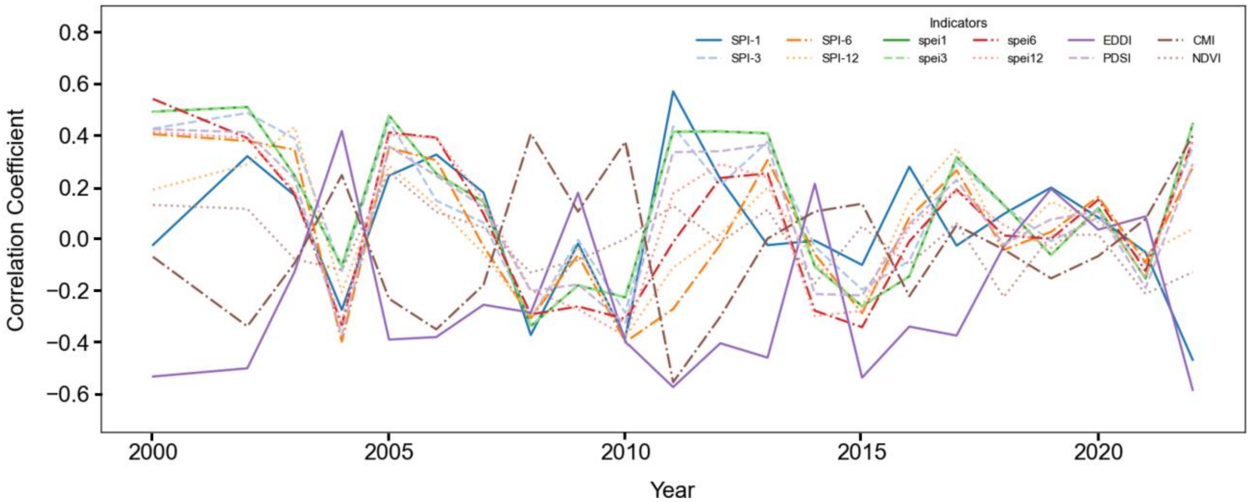

Figure 4: Annual correlation of soybean yield with different drought indices.

Figure 4 illustrates drought indices and soybean yield correlations from 2000–2022. These include the SPI for 1, 3, 6, and 12 months, the SPEI for similar durations, and the EDDI, PDSI, and Crop Moisture Index. The hue and style of each line reflect how climatic conditions impact soybean production. Some years indicate significant effects of moisture and evaporative demand on soybean productivity. There are apparent early fluctuations, particularly around 2005, where the association between SPEI-12 and PDSI decreased. From 2010 to 2015, climate trends shifted substantially, affecting yields. After 2015, positive associations increased, notably with the shorter-term SPI and SPEI, indicating that the quick precipitation change effect yields more. This correlation analysis reveals the complex link between soybean yields and many environmental indicators, emphasizing the necessity to combine drought and climate data for better forecasting and agricultural planning.

Over 2000–2022, the mean correlation of each drought index for corn and soybeans shows the strongest and least correlation coefficient values in Figure 5. Hatched bars represent soybeans, and grey bars represent corn. A good connection between soybean yields and SPI-6, SPI-12, SPEI-6, and SPEI-12 suggests that these indices may be reliable soybean productivity forecasts. Corn yields are less regular and negatively correlated with EDDI. A negative correlation in the index means it doesn't describe the relationship between water availability and productivity well. Corn yields decrease with higher EDDI test results, which indicate severe dryness. These data suggest corn is more drought-prone than soybeans. Figure 5 shows the mean correlation coefficients between drought indicators and corn and soybean yields from 2000 to 2022. It also displays the contrasting climate sensitivities of corn and soybeans by evaluating the patterns in several drought indices. When applied to identical input values, the index yields varying results, suggesting that soybeans respond well to longer-term moisture indicators, whereas corn is more susceptible to drought. The results show that corn and soybeans are sensitive to drought differently. This shows how important it is to make crops more resistant to climate change, such as creating drought- and heat-tolerant varieties, using efficient irrigation methods, and changing when crops are planted to help them handle the harmful effects of climate change.

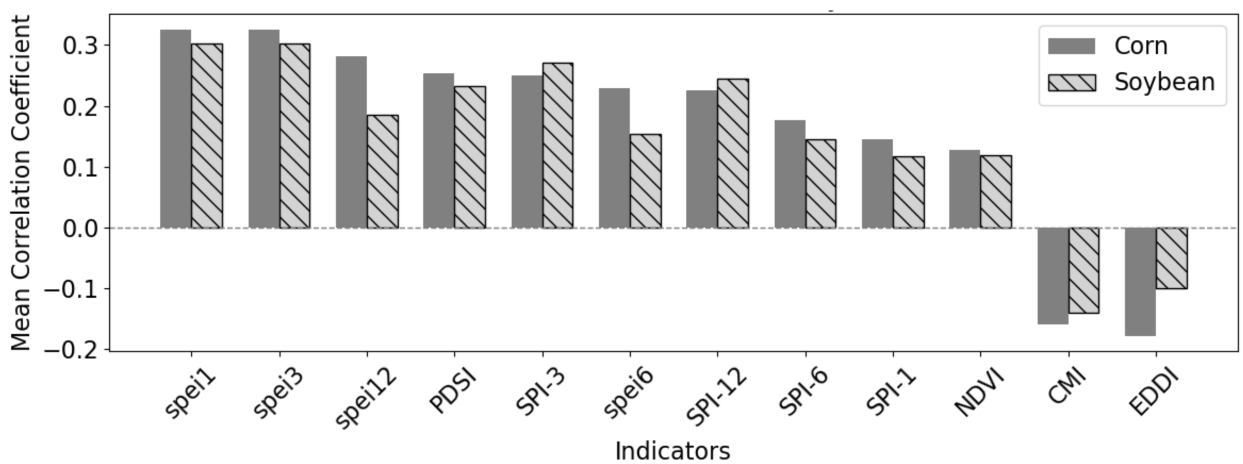

Figure 5: Mean correlation coefficient for corn and soybean yields.

Moreover, SPI-1 (Standardized Precipitation Index with a 1-month lag) is negatively correlated with soybean yields, indicating that lower SPI-1 values are associated with higher soybean yields. This suggests that short-term SPIs (SPI-1 and SPI-3) have minimal impact on soybean yields but significantly affect corn yields, likely due to soybeans' susceptibility to dryness during critical growth phases. Conversely, SPI-3 and SPI-6 (3- and 6-month lags) show a positive correlation with both corn and soybean yields, indicating that higher values of these indices are associated with higher yields for both crops. These findings highlight the importance of using appropriate drought indices for different crops to develop effective agricultural planning and risk management strategies. The association is more significant for soybean yields, especially SPI-6. This suggests that SPI-6 shows a good correlation for both crops, but soybeans benefit more from continuous wet circumstances. SPI-12 (12-month lag) and SPEI-12 positively correlated with corn and soybean yields.

These long-term metrics show that both crops need continuous rainfall to yield well. These long-term metrics indicate that corn and soybeans benefit from continuous rainfall during their respective growing seasons to yield well. The significant positive associations suggest favorable moisture conditions throughout the growing season, rather than the entire year, are crucial for boosting crop output. The EDDI (Evaporative Demand Drought Index) positively correlates with corn yields but not soybean yields. This is likely because corn is more sensitive to drought stress during critical developmental phases and requires more water than soybeans; therefore, high evaporative demand can be more detrimental to corn. Each drought index uses a different temporal basis, which may impact the results, highlighting the importance of selecting the appropriate index for accurate assessment and effective agricultural planning. Both crops have a strong positive connection with the PDSI (Palmer Drought Severity Index), demonstrating that soil moisture is crucial for crop productivity.

Figures 6 and 7 display all Iowa stations' averaged SPI-3, SPEI-3, and PDSI values from 2000 to 2022, respectively, as those have shown better corn and soybean yield results. SPI-3 (blue line) shows 3-month precipitation anomalies, whereas SPEI-3 (orange line) includes temperature impacts and adjusts for precipitation and evapotranspiration. Positive values indicate wetter circumstances, whereas negative values indicate drier conditions. The illustration shows how both indexes change over time, suggesting their possible effects on corn and soybean yields. Corn is more sensitive to drought during crucial growth phases and may be more affected by negative index values, while soybeans may be resilient depending on timing and severity.

Figure 6: SPI-3 and SPEI-3 values averaged at all stations from 2000 to 2022.

Much like SPI-3 and SPEI-3, PDSI effectively identifies extreme climatic events, delineating dry and wet conditions in Figure 7. A PDSI value of three or higher indicates wet conditions, while a negative three or lower value unequivocally signifies dry conditions. Notably, both figures (Figure 6 and Figure 7) robustly pinpoint 2012 as a particularly significant drought year.

The U.S. National Drought Mitigation Center's study in July 2012 revealed that about 87% of soybeans cultivated in the U.S. were produced in regions affected by drought, as indicated by historical NASS crop production statistics (USDA, 2012). In addition, on July 31, 2012, Iowa's drought coverage nearly reached 100% throughout the reproductive stage of soybeans, from flowering to setting pods.

Figure 8 shows Iowa's Standardized Precipitation Index (SPI-3) drought pattern from 2000 to 2022. The Standardized Precipitation Index-3 (SPI-3) is a standard drought index that measures three-month precipitation variations. Short-term drought conditions are accurately assessed. The figure comprises 23 year-specific maps. The legend colors are severe drought (red), moderate drought (orange), near normal (yellow), wet (light green), and very wet (dark green). These classifications show the state's drought intensity and geographical patterns over the selected period. The image shows that Iowa's drought has fluctuated dramatically. 2003, 2012, and 2020 saw widespread severe and moderate droughts, indicating persistent dryness. In 2008, 2010, and 2014, large parts of the state received plentiful rainfall, indicating sustained excessive precipitation. Different state regions show variances in spatial patterns. The intense droughts in 2012 and 2020 affected the south and west of Iowa, whereas the abundant rainfall in 2008 and 2010 was distributed more evenly.

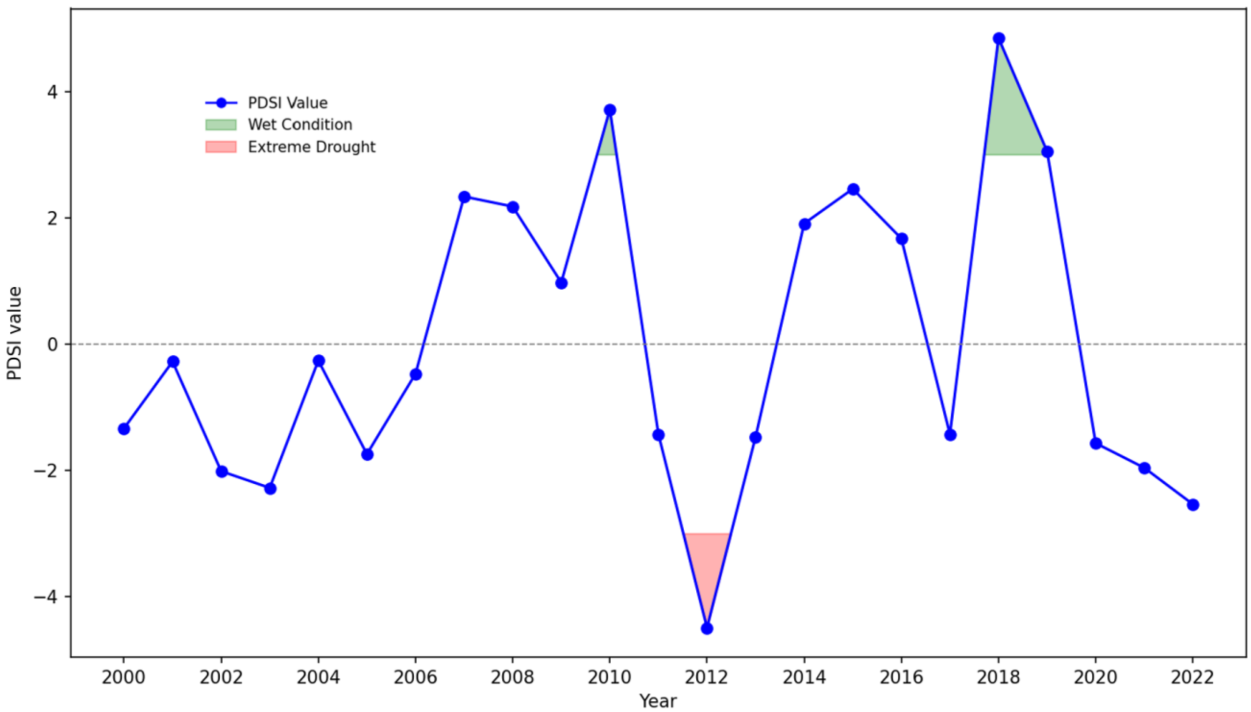

Figure 7: PDSI values averaged at all stations from 2000 to 2022.

Figure 9 illustrates Iowa's 2000–2022 Standardized Precipitation-Evapotranspiration Index (SPEI-3) drought spatio-temporal distribution. The SPEI-3 index integrates precipitation and potential evapotranspiration better to evaluate drought severity with temperature and atmospheric moisture demand. The picture shows annual maps grouped by drought severity: extremely dry (dark red), severely dry (red), moderately dry (yellow), normal (light green), and wet. SPEI-3 data shows patterns similar to SPI-3 but with some differences. In 2012, substantial portions of the state were exceedingly and severely dry, especially in the southwest and central regions, aggravated by high temperatures and increased evapotranspiration.

In contrast, 2010 and 2014 were wet seasons, supporting the SPI-3 findings but stressing the significance of temperature in reducing or amplifying drought impacts. There were relatively dry patches in 2007 and 2017, which indicates that regional climate change affected localized drought occurrences. The continuous green regions in 2000, 2008, and 2016 imply average or above-average moisture availability throughout both indices, indicating flooding.

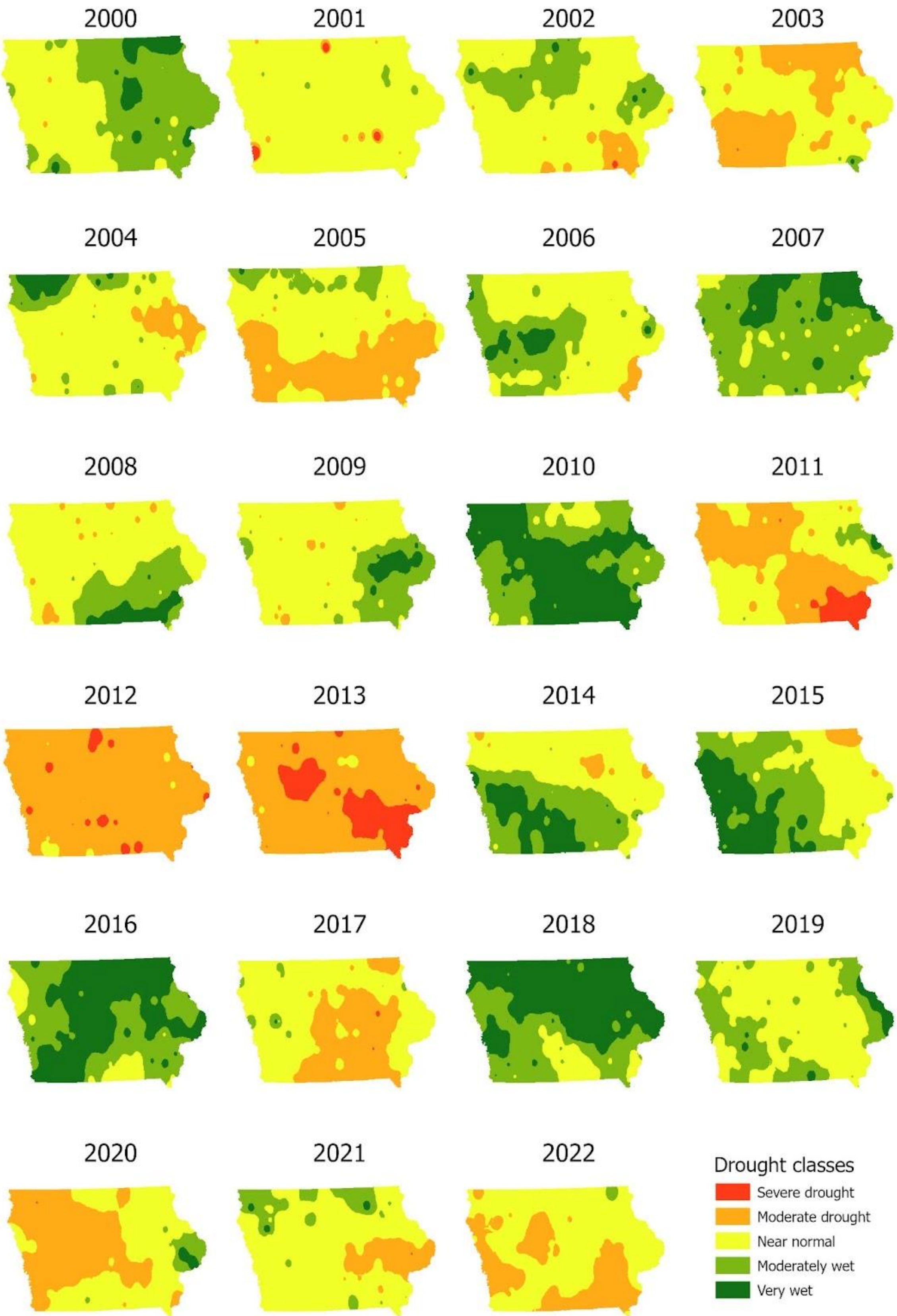

Figure 8: Spatio-temporal distribution of SPI-3 drought conditions in Iowa during 2000–2022.

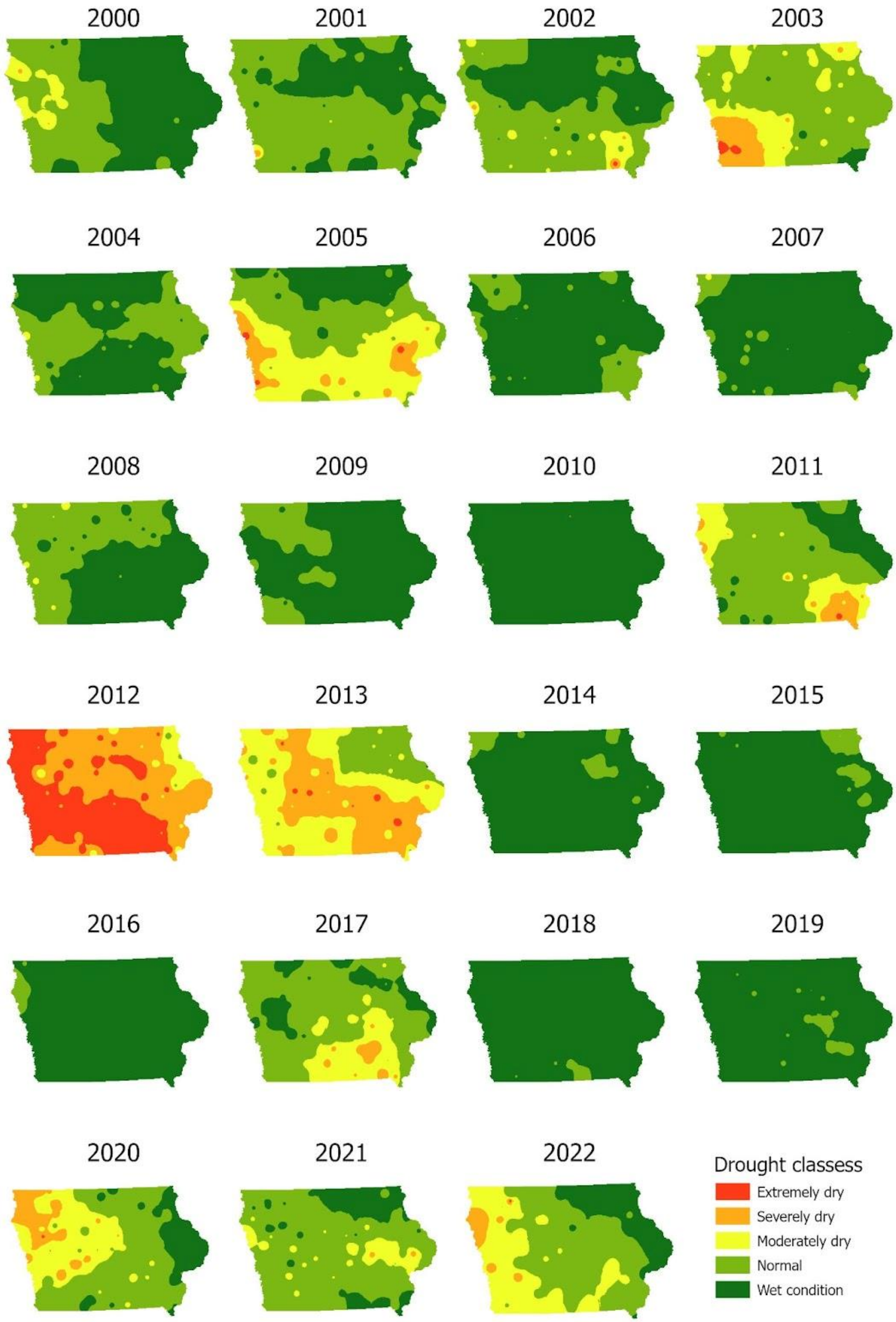

Figure 9: Spatio-temporal distribution of SPEI-3 drought conditions in Iowa during 2000-2022.

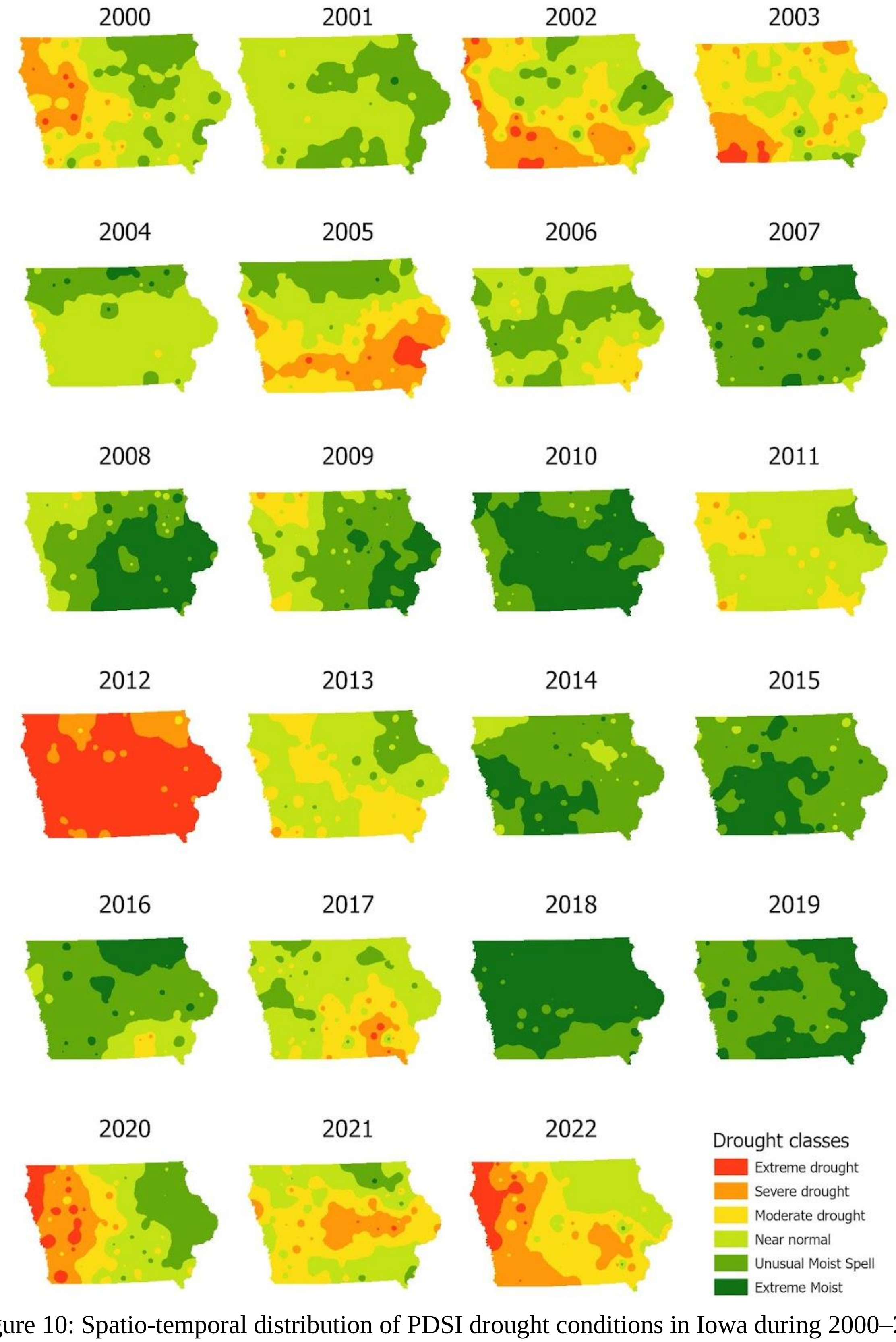

Figure 10: Spatio-temporal distribution of PDSI drought conditions in Iowa during 2000–2022.

Figure 10 shows the spatial and temporal pattern of the PDSI drought conditions. The PDSI is a commonly used index that combines temperature and precipitation data to assess the overall impact of drought and wetness over an extended period. This allows for a better understanding of long-lasting drought episodes and their effects on water resources. The diagram exhibits yearly maps classified into six drought categories: extreme drought (dark red), severe drought (red), moderate drought (orange), near normal (yellow), rare moist spell (light green), and excessive moist (dark green). The PDSI data shows parallels and differences compared to the SPI-3 and SPEI-3 indices. Significantly, 2012 is notable for having large areas experiencing extreme and severe drought, especially in the state's southern portion. This validates the insights drawn from the SPI-3 and SPEI-3 analyses while emphasizing the prolonged duration of this drought event.

In the same way, the year 2003 exhibits substantial regions facing severe and moderate drought, emphasizing a noteworthy period of aridity throughout that timeframe. In contrast, years like 2008 and 2010 demonstrate significant areas of the state characterized by uncommon periods of high moisture and extreme wet conditions, indicating periods of plentiful rainfall. This corresponds to the moist circumstances observed in SPI-3 and SPEI-3 data, further strengthening the connection among several drought metrics. The spatial distribution in years such as 2006 and 2015 indicates the presence of mild drought in specific locations, indicating localized dry conditions that regional climate anomalies may influence. Furthermore, green regions in 2014 and 2016 indicate sufficient moisture, suggesting that these years saw wetter conditions than usual.

4. Conclusions

This research investigates conventional and satellite-based drought indices used to assess the impact on corn and soybean yield during the cropping period in Iowa between 2000 and 2022. Various widely employed drought indices, particularly those related to precipitation and potential evapotranspiration and satellite-based indices, are considered in this analysis. It also analyzed the effects of drought on corn and soybean yields. The data indicates a high frequency of intense drought episodes (in 2003, 2012, 2013, 2020, and 2022) throughout the agricultural cycle. This research also showed that the detrended standardized output residual series (SYRS) accurately depicts the annual fluctuations in crop output for both corn and soybean. It was observed that the crop growth phases for corn and soybeans are most strongly connected with the SPI-3, SPEI-3, and PDSI, and they indicate the specific time when water deficiency has the most significant impact on crop growth.

Furthermore, variations in soil moisture across various geographies indicate drought might induce water scarcity, leading to reduced agricultural output. This analysis aimed to assess the effects of widely used drought indices on crop output. When compared to other indices, SPI-3 and SPEI-3 showed a stronger correlation between corn and seasonal drought. On the contrary, the Palmer Drought Severity Index (PDSI) exhibited a stronger association with soybeans as time progressed. Research shows that the SPI-12 and SPEI-12 indices indicate long-term moisture conditions affecting agricultural yields. The medium-term index, including the SPI-3 and SPI-6, is crucial for evaluating soybeans.

On the other hand, indications of drought stress, such as EDDI, harm corn yields. These findings highlight the significance of consistent moisture for crop productivity across the growing season and can enhance agricultural water management and mitigate drought. The findings indicate that drought has transpired throughout various stages of crop growth, leading to a subsequent impact on crop productivity across diverse regions of Iowa. While the findings solely focus on climate variability conditions, they contribute to a better comprehension of drought progression in Iowa. Consequently, the outcome can assist in assessing the impact of drought on soybean production at various growth stages. It can provide valuable supplementary information for making decisions about drought relief, crop management, and grain trading. This information can help plan and prepare for future drought conditions in advance.

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