Assessment of Drought Impacts on Crop Yields (Corn and Soybeans) Across Iowa During 2000 – 2022

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Abstract

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Introduction

Food production is a cornerstone of food security, directly influencing the availability of essential resources necessary for sustaining life. Food security encompasses multifaceted dimensions, including production, availability, access, utilization, and stability over time (Capone et al., 2014). Agricultural productivity is influenced by a combination of factors, such as temperature and precipitation, which affect crop development, health, annual yields, and the long-term productivity of cropping systems (Howden et al., 2007; Liang et al., 2017; Ray et al., 2018). In Iowa, corn and soybeans are vital for food and biofuel production, with corn serving as a key feedstock for ethanol and soybeans for biodiesel. Climate change exacerbates these challenges, increasing the frequency of climatic extremes and their adverse impacts on agricultural production (Gornall et al., 2010; Vogel et al., 2019; Alabbad et al., 2023). Numerous studies have investigated the impact of climate change on agriculture across various geographical levels (Kang et al., 2009; Olesen et al., 2011; Parry et al., 2004). However, most have not explicitly focused on the interaction between hydrological extremes—such as droughts and floods—and crop production. Understanding these opposite but equally disruptive events is critical for designing adaptive strategies to mitigate adverse effects and improve cropping systems. This omission leaves a gap in understanding the specific links between drought conditions and agricultural yields. Drought, a complex natural phenomenon, profoundly impacts global environmental, societal, and economic domains, posing significant challenges to sustainable agriculture. Regions like Iowa, heavily reliant on rain-fed systems, are particularly vulnerable (Haile et al., 2020; Islam et al., 2022, 2024; Savelli et al., 2022; Sen, 2015; Yesilkoy et al., 2023). Forecasted climate changes predict an increase in extreme weather events, including droughts, which impact water resources, population health, economic stability, and crop production (Cikmaz et al., 2023; Field, 2012; Raymond et al., 2020; Sivakumar & Stefanski, 2011; Yildirim et al., 2024). Anthropogenic activities and climate change have intensified drought unpredictability and severity, permanently damaging sensitive agroecosystems, increasing crop losses, and exacerbating pest and disease outbreaks (Mahdi et al., 2015; Subedi et al., 2023; Tadele, 2017; Yildirim et al., 2022). For example, the flash drought in the U.S. Central Great Plains in 2012—the most severe since 1930—caused agricultural losses exceeding $20 billion (Fuchs et al., 2012; Hoell et al., 2020; Hoerling et al., 2014). Such extreme events underscore the urgent need for effective drought management strategies and the development of resilient agricultural systems. As a leading producer of corn and soybeans, Iowa is particularly susceptible to climate variability due to its dependence on favorable climatic conditions, high soil quality, and sufficient water availability (Grassini et al., 2015; Kukal & Irmak, 2018). Between 1989 and 2022, drought-related crop insurance claims in Iowa alone amounted to over $5.3 billion, illustrating the substantial economic toll of drought (Beach et al., 2010; Maisashvili et al., 2023). 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. Despite its critical importance, limited research has explicitly investigated drought impacts on agricultural production in Iowa within the context of climate change. Addressing this gap, this study aims to evaluate the extent of drought's impact on agricultural yields using indices that incorporate both temperature and precipitation, which are critical for computing potential evapotranspiration. This approach offers a pathway to mitigate drought's effects and establish a sustainable farming system for optimal agricultural output. The urgency of this research is underscored by the increasing frequency of extreme weather events, including droughts, and their adverse impacts on agricultural production. Immediate action is needed to address this issue and ensure the future of agricultural management. Several indices have been developed to assess drought impacts, each leveraging distinct environmental data. Commonly used indices include 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). While PDSI evaluates water balance over specific periods, its limited ability to capture short-term droughts reduces its applicability for meteorological and agricultural assessments. On the other hand, SPI focuses solely on precipitation but provides flexibility across varying timescales for meteorological, agricultural, and hydrological purposes (Laimighofer & Laaha, 2022; McKee et al., 1993). SPEI combines precipitation and temperature data, making it more suitable for assessing the impacts of climatic changes on drought (Ma et al., 2014; Vicente-Serrano et al., 2010). Recent studies have demonstrated the utility of SPEI for evaluating drought impacts on crops globally (Potop et al., 2012; Ribeiro et al., 2019; Tian et al., 2019). In addition to these indices, this study considers the Evaporative Demand Drought Index (EDDI), developed by NOAA, which serves as an early warning indicator by assessing atmospheric dryness (Hobbins et al., 2016; McEvoy et al., 2016). Other indices, such as the Normalized Difference Vegetation Index (NDVI) (Krieger, 1969) and the Crop Moisture Index (CMI) (Juhasz & Kornfield, 1978), were also analyzed to determine their suitability in assessing drought impacts on crop yields in Iowa. This study examines the correlation between drought indices and yields of Iowa's primary crops, corn, and soybeans, during 2000–2022. By leveraging multiple datasets, including temperature, soil moisture, evapotranspiration, and rainfall, the research provides comprehensive insights into the interplay between drought and crop yields. The findings aim to guide future agricultural practices and policies, enhancing resilience and sustainability in Iowa's agricultural sector.

Materials and Methods

This study focuses on Iowa, utilizing secondary atmospheric and spatial data to analyze the effects of drought on corn and soybean yields. Statistical analyses and GIS tools were combined to examine numerical data and geographical patterns. Detailed justifications for data selection, preprocessing steps, and analysis methods are provided to enhance transparency and reproducibility.

Study Area

The study area includes Iowa, an agriculturally dominant region in the U.S., where 85% of the land is dedicated to farming (Bell, 2010). The state produces essential crops like corn and soybeans, supported by its fertile loess soils, flat terrain, and a continental climate characterized by hot summers and cold winters (Islam et al., 2024).

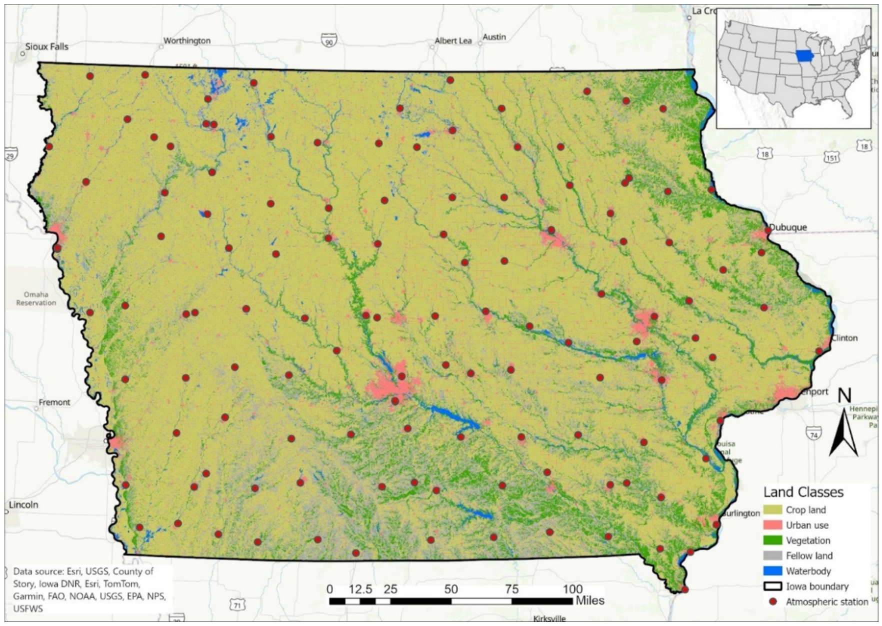


Figure 1: Land use and land classification map of Iowa. The map, derived from the USDA's Cropland Data Layer (CDL), highlights the distribution of key agricultural regions, with classifications for corn, soybeans, and other land uses. The CDL's pixel-level accuracy exceeds 80% for primary crops such as corn and soybeans.

Data and Methods

The study utilized data from 126 meteorological stations across Iowa, chosen for their comprehensive and consistent data availability. These stations monitor key atmospheric variables, including rainfall, temperature, humidity, and solar radiation. Additionally, land cover data were obtained from the USDA's Cropland Data Layer (CDL), which provides raster-based classifications of land use. Each pixel in the CDL is categorized based on land-use type, with an accuracy exceeding 80% for primary crops such as corn and soybeans (Boryan et al., 2011; Johnson et al., 2010). Data integration involved matching the spatial resolution of the meteorological data with crop-specific land cover maps using interpolation techniques.

Crop Yields

Crop yield data for corn and soybeans from 2000–2022 were obtained from USDA's NASS Quick Stats database (USDA, 2023). These yields represent statewide averages based on field surveys, farmer reports, remote sensing, and statistical modeling. While statewide yields were used for this analysis, future studies could investigate finer-scale yield data to differentiate between irrigated and non-irrigated crops, as irrigation practices can significantly influence drought resilience.

Standardized Residual Yield Series (SRYS)

A linear regression approach was applied to detrend crop yield data to account for technological advancements and climate adaptations influencing yield trends. The residuals from this regression, termed the Standardized Residual Yield Series (SRYS), represent deviations attributed to weather variability (Liu et al., 2018). SRYS is calculated as follows:

$$SRYS = \frac{y_i - \mu}{\sigma} \quad \ldots\ldots\ldots\ldots (1)$$

A sensitivity analysis was conducted to evaluate SRYS's robustness against variations in regression parameters, addressing potential uncertainties related to its use in interpreting weather impacts. This ensures that SRYS reliably isolates the effects of weather from long-term technological improvements.

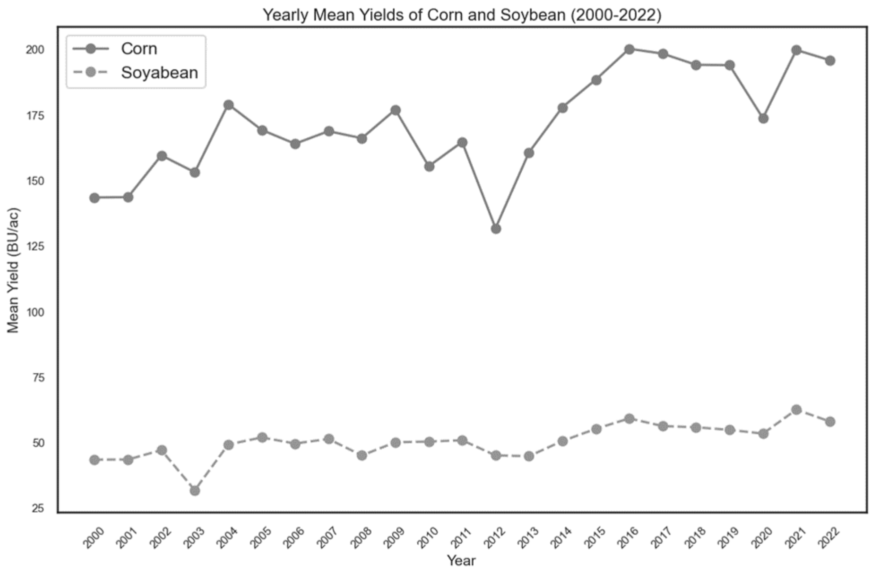


Figure 2: Mean yearly corn and soybean yields in Iowa between 2000 and 2022.

Drought Indices

This study utilized six drought indices to capture various dimensions of drought and their potential impacts on crop yields. The indices were selected based on their ability to represent short-term and long-term drought conditions. Each index is described below, along with its limitations and rationale for inclusion.

Standardized Precipitation Index (SPI)

SPI quantifies precipitation deficits or surpluses over multiple timescales, such as 1, 3, 6, and 12 months (McKee et al., 1993). Contrary to earlier statements, SPI values can range widely but typically fall between -3.0 and +3.0, with negative values indicating drought conditions and positive values indicating wet conditions. Precipitation data from the Iowa Mesonet (https://mesonet.agron.iastate.edu/) were used to calculate SPI values.

Standardized Precipitation Evapotranspiration Index (SPEI)

SPEI combines precipitation and potential evapotranspiration (PET) to better account for temperature effects on drought (Vicente-Serrano et al., 2010). SPEI values were derived using the SPEI R package, incorporating monthly precipitation and temperature data. SPEI is particularly useful for capturing the combined impact of temperature and rainfall, a critical factor for agricultural applications.

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.

$$D_i = P_i - PET_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

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. The SPEI R package may be accessed at http://cran.r-project.org/web/packages/SPEI. Di was fitted using the logarithmic distribution function f(x) in Equation (3). The SPEIs were derived from numerous time series, including SPEI-1, SPEI-3, SPEI-6, and SPEI-12, using Equation (4):

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

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

$$SPEI = W - \frac{c_o + c_1 W + c_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \qquad W = \sqrt{-2\ln(P)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (4)$$

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).

Palmer Drought Severity Index (PDSI)

PDSI measures long-term drought using local temperature and moisture data (Palmer, 1965). While helpful in assessing prolonged droughts, PDSI has limitations in reflecting short-term droughts due to its lagging nature. Monthly observations from 126 meteorological stations were used to calculate PDSI values.

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 considering 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 (incredibly moist conditions), making it helpful in tracking prolonged drought or wet spells.

$$PDSI = 0.897PDSI_{i-1} + \frac{1}{3}Z_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

$$Z_i = K_i d_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

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).

Evaporative Demand Drought Index (EDDI)

EDDI evaluates atmospheric potential for evaporation, offering early warnings for drought onset (Hobbins et al., 2016). It is susceptible to atmospheric dryness and complements other indices by providing insights into potential drought development.

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 formula:

$$P(E_{oi}) = \frac{i - 0.33}{n + 0.33} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

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 by the inverse version of the normal distribution function, i.e.:

$$EDDI = W - \frac{c_o + c_1 W + c_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

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.

Crop Moisture Index (CMI)

CMI assesses weekly crop conditions using precipitation and temperature data. As a short-term index, CMI provides valuable insights into rapidly changing crop moisture conditions (Palmer, 1968). 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).

Normalized Difference Vegetation Index (NDVI)

NDVI uses satellite imagery to assess vegetation health by measuring the difference and sum of near-infrared (NIR) and red light (R) reflectance. While NDVI was calculated for this study, it was excluded from the correlation analysis due to its sensitivity to cloud cover, which introduces noise in time series data. NDVI values, ranging from -1.0 to +1.0, were derived from MODIS satellite data using standard preprocessing steps (Rouse Jr et al., 1974).

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). MODIS MOD13Q1 data was used for the index quantification. 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 formula:

$$NDVI = \frac{NIR-R}{NIR+R} \ldots\ldots\ldots\ldots\ldots\ldots (9)$$

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.

Table 1: Name of the indices and data sources.

Name of the Index	Data required	Data source
Different SPI time scales	SPI-1 SPI-3 SPI-6 SPI-12	Monthly precipitati
Different SPEI time scales	SPEI-1 SPEI-3 SPEI-6 SPEI-12	Monthly precipitati
PDSI	Monthly precipitation and temperature data, soil water holding capacity	Iowa Mesonet websi
EDDI	Temperature, relative humidity, wind speed, and solar radiation data	Iowa Mesonet websi
CMI	Weekly precipitation and temperature data	Iowa Mesonet websi
NDVI	Satellite imagery data (visible and near-infrared light)	Satellite data provi

Quantifying Correlation Analysis

The relationships between drought indices and crop yields were analyzed using Spearman's rho correlation coefficient. This non-parametric method was chosen to account for potential non-linear relationships. Statistical significance was determined at p<0.05p < 0.05p<0.05. Limitations of satellite-based indices, such as uncertainties in NDVI and SPEI compared to ground-based measurements, were considered in interpreting results.

Results and Discussion

This chapter presents the correlations between drought indices and crop yields, their spatio-temporal variability, and the implication for understanding drought impacts on agricultural productivity. The findings are discussed in detail to highlight the significance of both short- and long-term drought indices for corn and soybean yields. Insights into climatic conditions, spatial patterns, and implications for drought risk management are also explored.

Yearly Correlation of Corn Yields with Drought Indices

Figure 3 illustrates the yearly correlation coefficients between corn yields and various drought indices from 2000–2022. Shorter-term indices, such as SPI-1 and SPEI-1, exhibit greater variability in correlations, with significant swings in positive and negative values. These trends indicate that corn production is susceptible to short-term precipitation variability, particularly during critical growth stages such as silking and grain filling. For instance, corn is highly reliant on moisture availability during its reproductive phase, and a lack of rainfall during these periods can result in substantial yield reductions. In contrast, longer-term indices like SPI-12 and SPEI-12 reflect the cumulative impact of extended moisture conditions. These indices capture broader seasonal or yearly precipitation trends, which align with the water requirements of corn during the entire growing season. Notably, sharp peaks and troughs in 2005, 2012, and 2018 correspond to years of significant climatic anomalies. For example, the severe drought of 2012, widely regarded as one of the most impactful droughts in U.S. history, resulted in significant negative correlations across most indices, underscoring the vulnerability of corn to prolonged droughts.

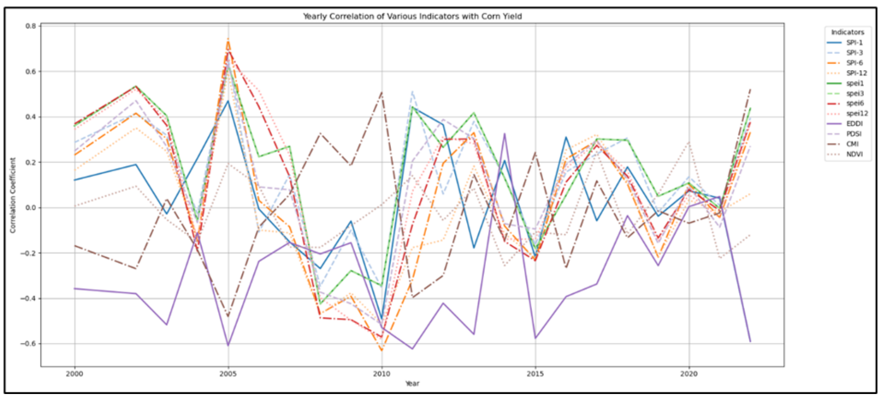


Figure 3: Annual correlation of corn yield with different drought indices.

Higher correlations observed for indices such as PDSI and EDDI during 2004 and 2010 suggest that these indices may more effectively capture specific drought dynamics during favorable or extreme weather conditions. The variability in correlation coefficients reflects the complex interplay between climatic variables and corn productivity. This underscores the importance of using multiple indices to understand drought impacts comprehensively. 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.

Yearly Correlation of Soybean Yields with Drought Indices

Figure 4 highlights the annual correlation coefficients between soybean yields and drought indices. Unlike corn, soybeans exhibit greater resilience to short-term indices such as SPI-1 and SPEI-1, as indicated by smaller fluctuations in correlation values. However, longer-term indices like SPI-6, SPI-12, SPEI-6, and SPEI-12 show stronger and more consistent correlations with soybean yields. This suggests soybeans benefit more from sustained moisture availability over extended periods, particularly during key growth stages like pod setting and filling.

The oscillations observed around 2005, 2012, and 2018 reflect the complex interaction between climatic conditions and soybean yields. For example, 2012, severe drought conditions led to negative correlations across most indices, although soybeans demonstrated slightly higher resilience than corn. This can be attributed to the crop's ability to recover from moderate drought stress during non-critical growth phases.

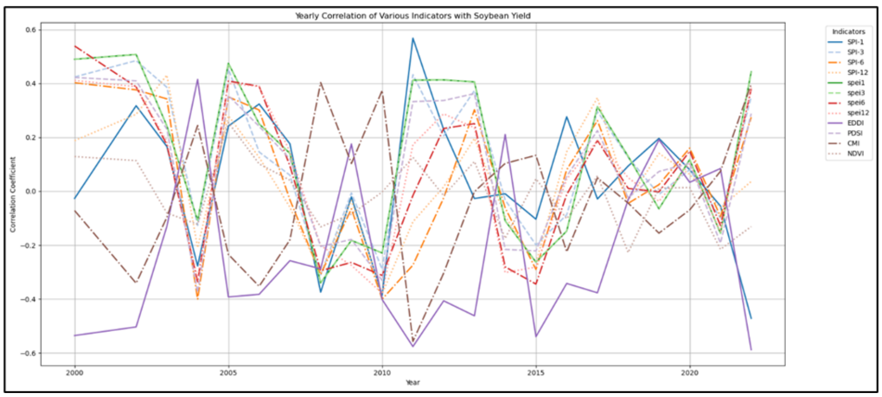


Figure 4: Annual correlation of soybean yield with different drought indices.

From 2010 to 2015, notable shifts in climatic trends influenced yield responses, as evidenced by increasing positive correlations with shorter-term indices. After 2015, the influence of rapid precipitation changes (as captured by SPI-1 and SPEI-1) became more apparent, emphasizing the need for adaptive management strategies that consider these dynamics.

Mean Correlation Analysis

Figure 5 presents the mean correlation coefficients for corn and soybean yields with all drought indices over the study period. Soybeans demonstrate stronger correlations with SPI-6, SPI-12, SPEI-6, and SPEI-12, highlighting their dependence on long-term moisture availability. These indices may serve as reliable predictors of soybean productivity in Iowa under similar climatic conditions.

In contrast, corn yields exhibit less consistent correlations with these indices, likely due to the crop's greater sensitivity to short-term drought conditions. Notably, EDDI shows a strong negative correlation with corn yields, reflecting the crop's susceptibility to high evaporative demand during critical growth phases. This aligns with corn's higher water requirements and sensitivity to drought-induced stress.

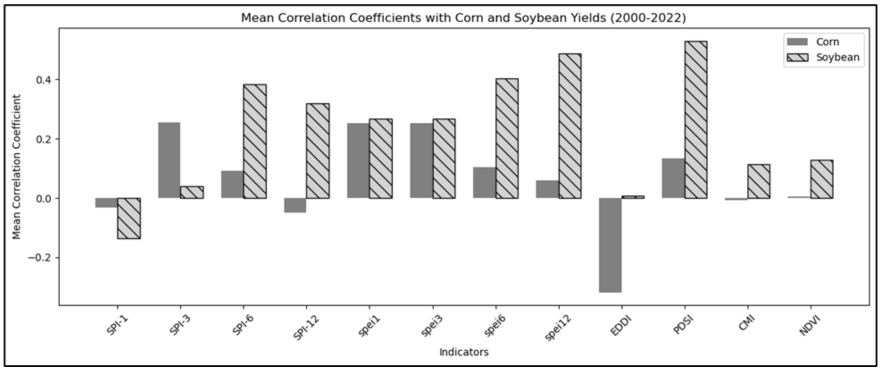


Figure 5: Mean correlation coefficients for corn and soybean yields.

The results also show that SPI-1 and SPEI-1 have limited predictive value for soybeans but significantly influence corn yields. These findings underscore the importance of selecting appropriate drought indices tailored to specific crops and growth stages to enhance drought forecasting and risk management strategies.

Spatio-Temporal Patterns of Drought Indices

Figures 6–11 illustrate the spatiotemporal distribution of SPI-3, SPEI-3, and PDSI values, providing insights into the geographical and temporal variability of drought impacts on crop yields in Iowa.

SPI-3 and SPEI-3 Trends

Figure 6 shows the temporal trends of SPI-3 and SPEI-3, capturing short-term precipitation anomalies and their combined temperature effects. Positive values indicate wet conditions, while negative values denote drought conditions. The 2012 drought is particularly notable, with severe negative values reflecting extreme dryness. Wet years, such as 2010 and 2014, correlate with increased crop yields, highlighting the critical role of moisture availability.

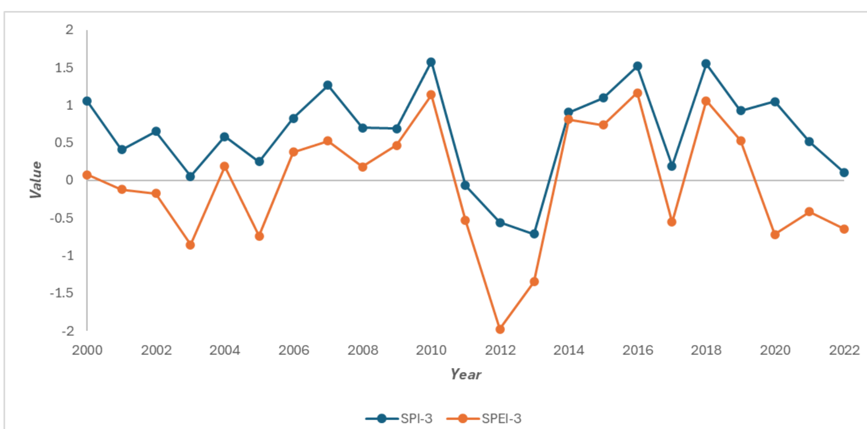


Figure 6: SPI-3 and SPEI-3 values averaged across all stations.

PDSI Temporal Trends

Figure 7 complements SPI-3 and SPEI-3 by capturing longer-term soil moisture anomalies. The 2012 drought stands out, with PDSI values reaching extreme lows, indicative of prolonged water deficits. Wet conditions in

2008 and 2010 demonstrate the index's ability to capture excessive moisture periods, which can also influence crop productivity.

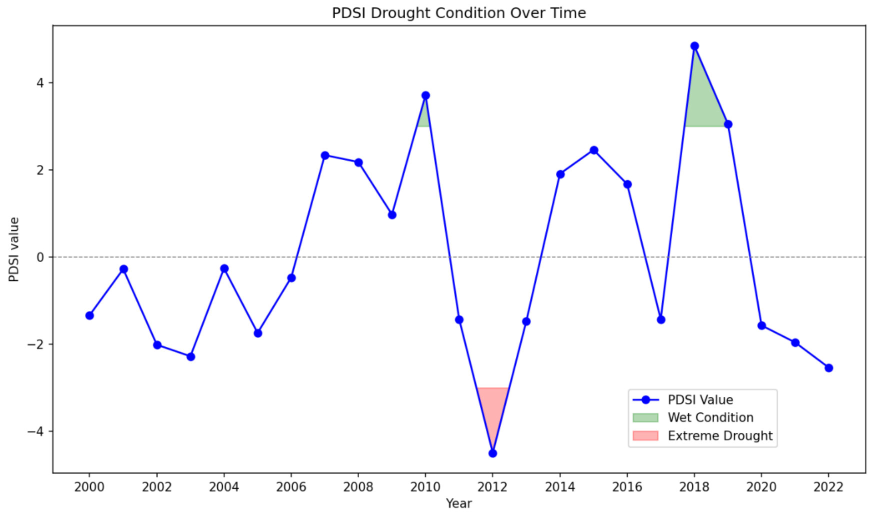
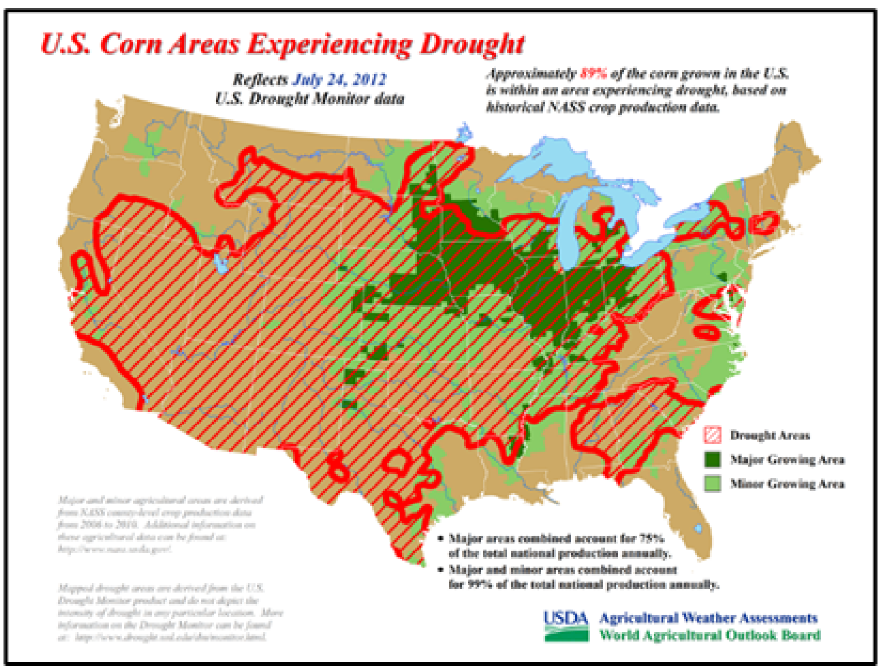


Figure 7: PDSI values averaged across all stations.



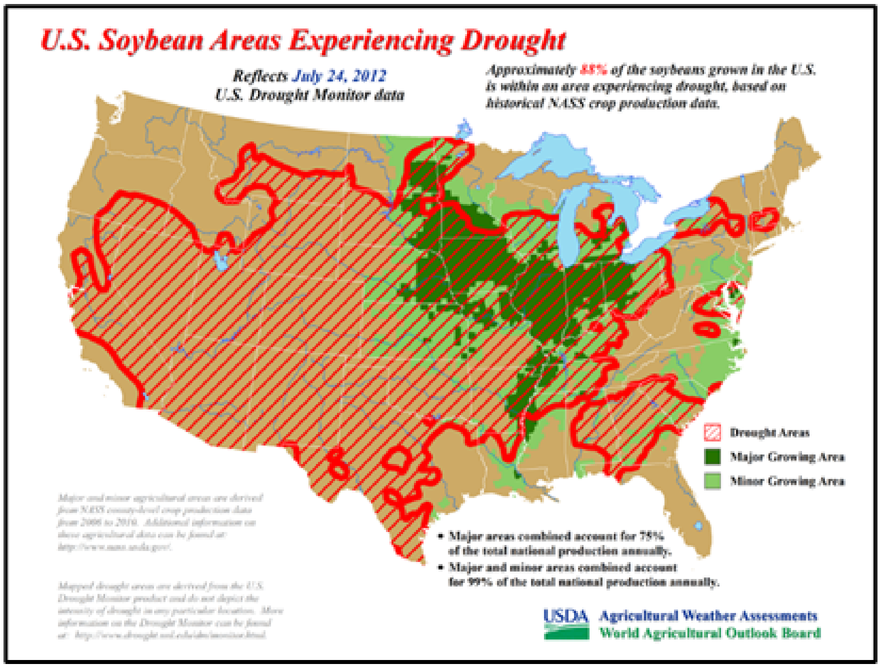


Figure 8: Corn and soybean areas experiencing 2012's drought in the US.

The U.S. National Drought Mitigation Center's study in July 2012 (Figure 8) 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.

Spatial Distribution Analysis

A detailed understanding of the spatial and temporal distribution of drought indices is essential for evaluating localized drought impacts on agricultural productivity. This subsection focuses on the spatio-temporal variability of key drought indices, including the Standardized Precipitation Index (SPI-3) and the Standardized Precipitation-Evapotranspiration Index (SPEI-3), across Iowa from 2000 to 2022. These indices provide critical insights into short-term precipitation anomalies and moisture demand, offering a comprehensive framework to assess trends, regional variability, and anomalies influencing crop yields over the study period.

Spatio-Temporal Patterns of Drought Indices

Figure 9 illustrates the spatial and temporal variability of the Standardized Precipitation Index (SPI-3) across Iowa from 2000 to 2022, providing insights into short-term precipitation anomalies. The maps reveal significant fluctuations in drought intensity, with severe and moderate droughts dominating 2003, 2012, and 2020, particularly in the southern and western regions. These patterns align with periods of persistent dryness, coinciding with notable yield reductions in these areas. Conversely, wet years like 2008, 2010, and 2014 show widespread excessive rainfall, which supported higher yields but also risked flooding, emphasizing the dual challenges of extreme moisture variability.

Figure 10 complements this analysis with the Standardized Precipitation-Evapotranspiration Index (SPEI-3), incorporating the effects of temperature and atmospheric moisture demand. While trends generally align with SPI-3, SPEI-3 highlights the amplified severity of droughts, particularly in 2012, due to elevated evapotranspiration. The index reveals critical differences during wet years like 2010 and 2014, underscoring the role of temperature in either mitigating or exacerbating drought impacts. Localized dry spells in 2007 and 2017 suggest regional climate variability influenced by changing atmospheric conditions.

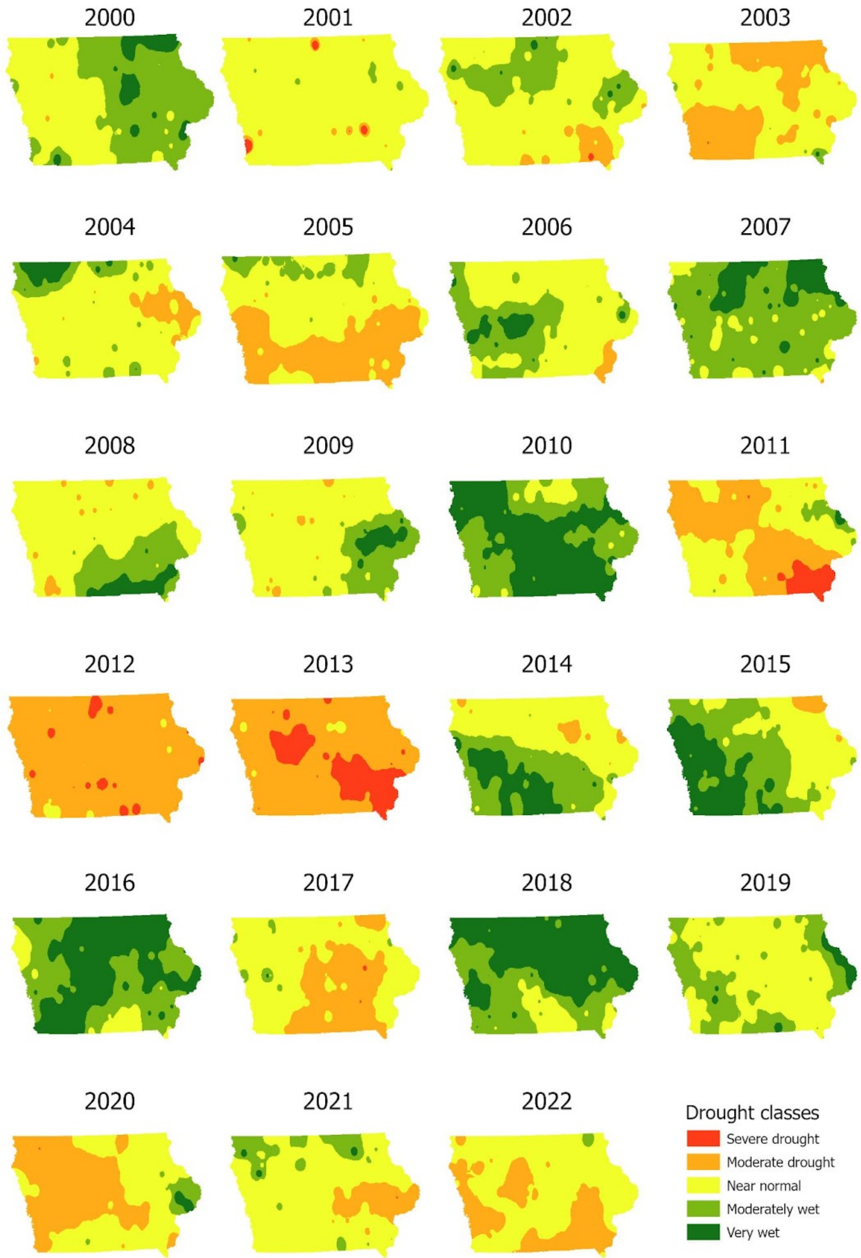


Figure 9: Spatio-temporal distribution of SPI-3 drought conditions in Iowa.

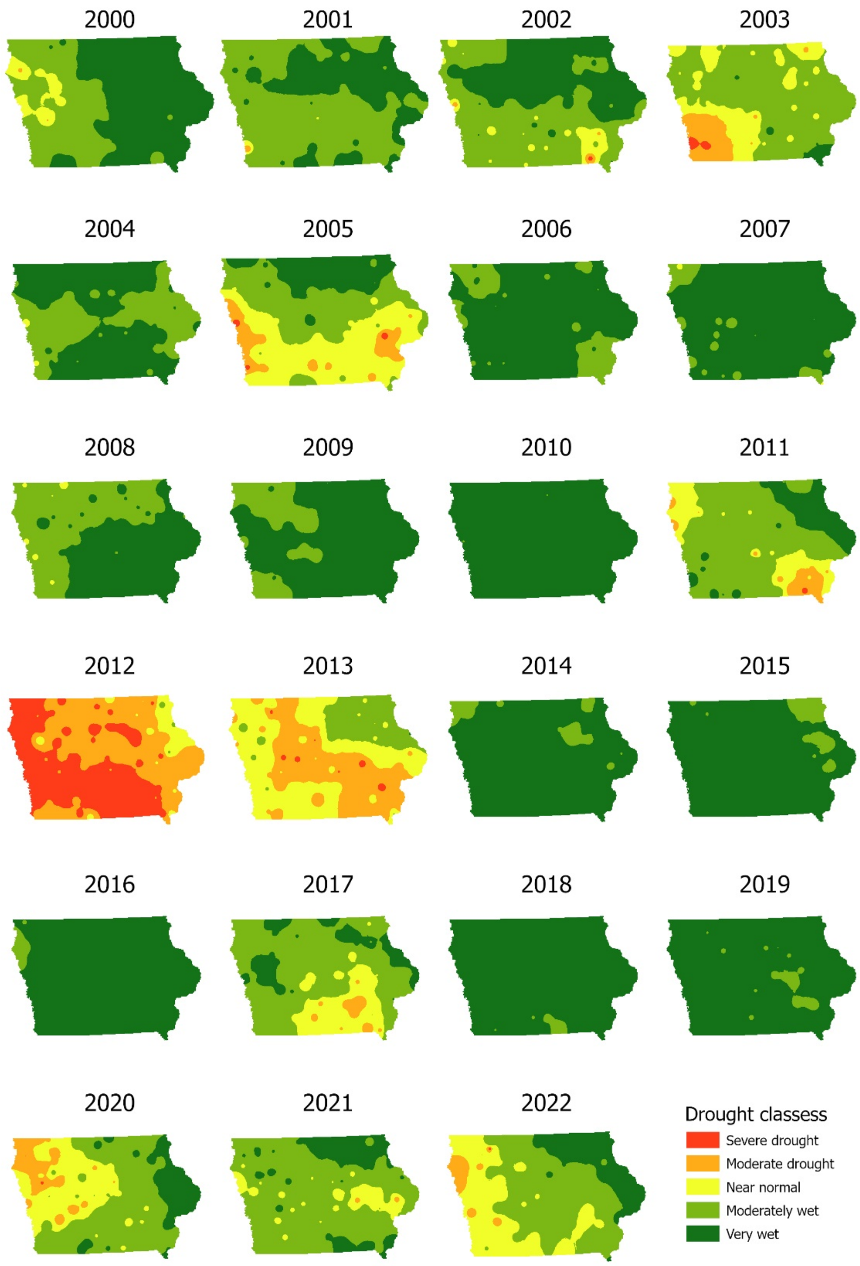


Figure 10: Spatio-temporal distribution of SPEI-3 drought conditions in Iowa.

Figure 11 presents the Palmer Drought Severity Index (PDSI), which reflects the cumulative effects of temperature and precipitation on soil moisture over extended periods. The PDSI confirms the prolonged nature of the 2012 drought, particularly in southern Iowa, while also identifying significant moisture surpluses in 2008 and 2010. These findings validate insights from SPI-3 and SPEI-3 while emphasizing PDSI's utility in understanding sustained drought and wetness impacts. Mild droughts in 2006 and 2015 and moisture surpluses in 2014 and 2016 further highlight localized variability, suggesting the influence of regional climate anomalies.

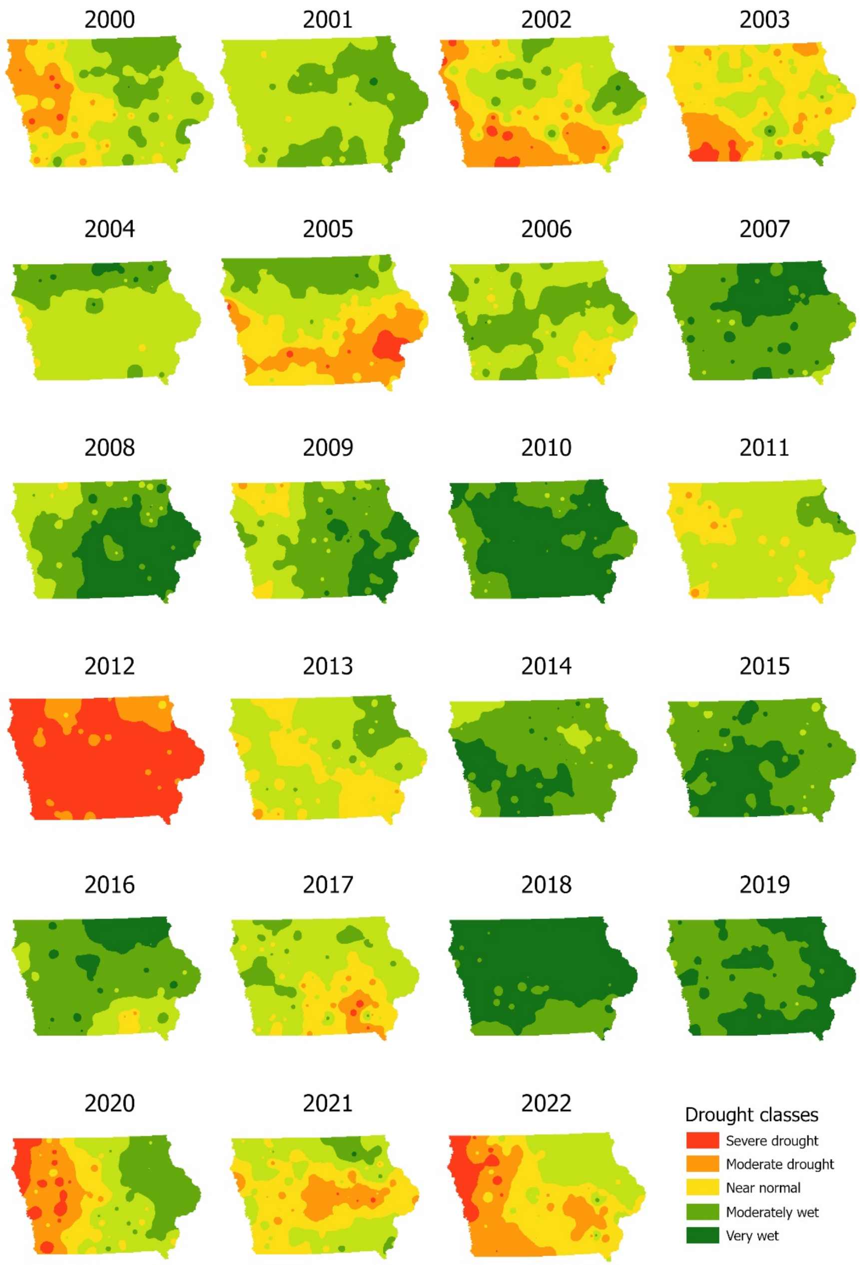


Figure 11: Spatio-temporal distribution of PDSI drought conditions in Iowa.

Discussions

The spatio-temporal analysis of these indices demonstrates their complementary roles in assessing drought impacts on crop yields. SPI-3 captures immediate precipitation anomalies, SPEI-3 incorporates temperature-driven evaporative demand, and PDSI reflects cumulative moisture conditions. The indices collectively highlight the temporal and spatial variability of drought impacts, with 2012 emerging as a critical year for agricultural productivity loss. The year was marked by prolonged precipitation deficits, elevated temperatures, and heightened evapotranspiration, which collectively exacerbated soil moisture depletion and hindered crop growth during critical developmental phases. This underscores the need for region-specific agricultural planning that considers the dual risks of drought and flooding.

These findings emphasize the importance of integrating multiple drought indices to develop resilient farming strategies. Future work should explore how these indices perform under changing climate scenarios, particularly with increasing temperatures and variability in precipitation patterns.

Conclusion

This research investigates the relationship between drought indices and crop yields, focusing on corn and soybean production in Iowa from 2000 to 2022. By analyzing both conventional and satellite-based drought indices, such as the Standardized Precipitation Index (SPI), the Standardized Precipitation-Evapotranspiration Index (SPEI), the Palmer Drought Severity Index (PDSI), and the Evaporative Demand Drought Index (EDDI), this study provides a comprehensive assessment of how climatic variability impacts agricultural productivity. These indices, applied at various temporal scales (1, 3, 6, and 12 months), capture the complex interplay of precipitation, evapotranspiration, and soil moisture dynamics in crop growth stages. The findings reveal a high frequency of intense drought episodes in 2003, 2012, 2013, 2020, and 2022, which had pronounced impacts on crop yields, particularly in Iowa's central, southern, and western regions. While drought is likely the primary driver of these yield reductions, other confounding factors, such as pest infestations, disease outbreaks, soil fertility variability, and management practices, could also have contributed to these fluctuations. Additionally, extreme weather events like heat waves during critical growth phases may have compounded the impacts of water deficiency. The detrended standardized yield residual series (SRYS) effectively isolated the effects of climatic variability, illustrating significant crop output fluctuations for corn and soybeans. These analyses identified SPI-3, SPEI-3, and PDSI as critical indices for detecting water deficiency during key growth phases, underscoring their utility in assessing drought impacts. Geographically, variations in soil moisture across Iowa's regions indicate drought conditions can induce severe water scarcity, particularly in areas with lower soil water-holding capacity. These spatial patterns emphasize the importance of integrating localized data into drought mitigation strategies. The results also demonstrate crop-specific sensitivities: SPI-3 and SPEI-3 exhibited stronger correlations with corn yields, effectively capturing the impact of short-term precipitation deficits on corn productivity. In contrast, soybeans showed a stronger association with PDSI, which reflects prolonged moisture availability, indicating that soybeans are more sensitive to cumulative soil moisture conditions over time. Medium-term indices, such as SPI-6 and SPEI-6, were particularly effective at capturing conditions that align with soybean growth and productivity, suggesting that these indices reflect the environmental conditions influencing soybeans rather than any intrinsic association with the indices themselves. This distinction highlights the value of selecting appropriate drought metrics based on the crop and its sensitivity to specific temporal scales of moisture variability. Furthermore, the findings indicate that EDDI, which measures evaporative demand, negatively impacts corn yields, reinforcing the crop's vulnerability to high-temperature stress during critical growth periods. These observations highlight the significance of maintaining consistent moisture levels across the growing season to enhance crop productivity. This study's insights can inform strategies to optimize water resource management and mitigate the adverse effects of drought on agriculture. The results of this study hold practical relevance for agricultural planning and drought management. While the integration of multiple drought indices enhances our understanding of drought dynamics, it is important to recognize that these indices are models with inherent limitations. Rather than providing absolute "truth," they offer complementary perspectives on drought impacts, such as short-term deficits (e.g., SPI-3) or cumulative moisture conditions (e.g., PDSI). These insights can guide adaptive strategies, including selecting drought-tolerant crops, optimizing irrigation, and aligning planting schedules with moisture availability. Decision-support systems, such as drought relief programs and crop insurance frameworks, can benefit from incorporating these findings to enhance risk aversion strategies and minimize economic losses. While this study primarily models historical environmental conditions, its insights into the differential responses of corn and soybeans to shortand long-term drought indices lay the groundwork for developing forecasting tools. Such tools could help farmers anticipate drought impacts and make informed decisions about crop selection, planting schedules, and resource allocation. Although predicting drought cycles and long-term climate variability is a complex challenge, integrating these findings with climate models and real-time monitoring systems could improve agricultural resilience and guide investments in climate-adaptive practices tailored to Iowa's regional needs. While this study provides valuable contributions, certain limitations should be acknowledged. The reliance on standardized drought indices derived from meteorological and satellite data introduces inherent uncertainties, particularly in regions with limited ground-based observations. Additionally, statewide yield averages may obscure localized variations in drought impacts, as factors like irrigation practices, soil properties, and crop management strategies can significantly influence outcomes. Future research should address these limitations by incorporating finer spatial resolutions and integrating field-level data. The findings highlight the need to examine the implications of climate change on drought-crop relationships. Rising temperatures and variable precipitation will challenge the utility of current drought indices. Real-time monitoring tools and precision agriculture can help farmers make adaptive decisions, but farming's inherent path dependencies mean risks cannot be entirely eliminated once planting decisions are made. These tools could mitigate risks during the growing season, but systemic feedback, such as market responses and price stability, must also be addressed. Future work should explore integrating real-time tools with crop insurance and government subsidies to reduce risk and sustain profit margins under changing climate conditions.

Conflict of interest

The authors declare that they have no conflict of interest.

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