Response to Reviewer 1 Comments

MS No.: hess-2024-245

Thank you, Dr. Jasmin Heilemann, for your thoughtful review of our manuscript. We sincerely appreciate the time and effort you dedicated to carefully evaluating our work and providing valuable comments and suggestions. Your insights have significantly contributed to improving the quality of our manuscript. We have addressed each of your comments accordingly, and our responses are provided below. Reviewer comments are highlighted in red, while our responses are in black.

General comments:

In general, it is an interesting paper within the scope of the journal that addresses the highly relevant issue of detecting socio-economic impacts of drought using biophysical indicators on a global scale. The paper proposes a Combined Drought Indicator (CDI), which is constructed by using single-input based drought indices (SPI, NDVI, SSI, STI) and performing a Principal Component Analysis (PCA). The authors show that the CDI outperforms the single-input drought indices in its ability to capture drought events observed in the global GDIS dataset.

While the paper presents a very relevant analysis with noteworthy results, what is currently missing from the paper is a discussion of the benefits of using the PCA method to construct the CDI. This discussion should include details of the benefits of PCA for the CDI, as well as a discussion of the applicability of the CDI for (regionalized) drought impact monitoring and prediction. Including this in the manuscript would significantly enhance the paper and give greater significance to the implications, with potential applications of the CDI beyond this paper. My specific comments are listed below.

Specific comments:

1. Title: Global analysis of sub-national droughts: “Sub-national” droughts sound misleading, as droughts are not constrained by national borders. If possible, rephrase as “droughts at sub-national scale”, or similar.

- Thank you for recommending a title change for the manuscript. We agree that the original title may have been somewhat misleading in reflecting the study's scope. As per your suggestion, we have revised the title to more accurately align with the analysis and findings presented. The new title is: “Global Assessment of Socio-Economic Drought Events at Sub-National Scale: A Comparative Analysis of Combined Versus Single Drought Indicators.”

2. Abstract: “Out of 2142 drought events in 2001-2021 recorded by GDIS, NDVI, SSI, SPI, and STI identified 1867, 1770, 1740, and 1680 drought events, respectively. […] CDI outperformed the other single-input-based drought indices and identified 1885 events.” Consider adding percentages or otherwise present convincing quantitative results that show the superiority of the CDI more directly.

Thank you for pointing this out. We agree that adding percentages alongside event counts will be helpful for readers to better understand the results. In the revised manuscript, the percentages have been included.

The revised sentence in the abstract is as follows, “Out of 2142 drought events in 2001-2021 recorded by GDIS, NDVI, SSMI, SPI, and STI identified 1867 (87.16%), 1770 (82.63%), 1740 (81.23%), and 1680 (78.43%) drought events, respectively.”

3. Fig. 1: It is a bit confusing to frame the “wet” conditions as drought categories. Would it be possible to find a different notion, e.g. moisture? Or Drought/Wetness category?

Thank you for your comment. We understand the concern regarding the terminology. However, the drought classes and categories used in our study are based on the Standardized Precipitation Index (SPI) (McKee et al.,1993), which is a widely accepted approach. This classification system, which includes both wet and dry conditions under a common drought/wetness scale, has been adopted by several major drought monitoring institutions, such as the National Drought Mitigation Center (USA) and the Australian Bureau of Meteorology. Accordingly, we have followed these established references.

A clarifying sentence has been included in the revised manuscript (Section 3.1, line 210-211), which reads: "The drought categories applied in this study follow the widely used SPI classification, originally developed by McKee et al. (1993)."

4. Lines 116-125: The topic of the paper are socio-economic impacts of droughts. However, socioeconomic impacts manifest very differently in different sectors. E.g., in the introduction, you mention urban areas/water shortages in dams (lines 25-36). The drought indices you chose (SPI, NDVI, SSI, STI) are mostly useful for the ag sector. Please elaborate on how this affects the results, and if/how the CDI can capture socio-economic impacts isen non-ag sectors, e.g. urban areas.

Thank you for this thoughtful. We agree that the socio-economic drought impacts vary significantly across sectors and that the indices used in our study, SPI, NDVI, SSMI, and STI, are more closely aligned with impacts on the agricultural and vegetation-related sectors.

To address this, we have revised the manuscript to better explain the broader relevance of CDI beyond the agricultural context. Specifically, we now emphasize that the CDI integrates multiple environmental variables (SPI, NDVI, SSMI, and STI), which collectively capture drought conditions with potential implications for non-agricultural sectors as well. For example, SPI and SSI are closely related to hydrological drought, which can impact urban water supply and reservoir levels, while STI may relate to energy demand, health, and heat stress in urban settings (Vicente-Serrano et al., 2012; Hao & Singh, 2015; Wang et al., 2020).

We have also added a discussion on future research directions, highlighting the need for sector-specific indicators and data (e.g., urban water demand, infrastructure vulnerability, or energy production) to enhance the socio-economic relevance of CDI. These changes have been added in the revised manuscript in the Discussion section (Line 625-630), as follows:

"The current CDI primarily reflects agro-environmental droughts due to the nature of its input indices. However, since it combines precipitation, temperature, soil moisture, and vegetation data, it may also capture broader drought signals relevant to urban systems, such as water availability and heat stress (Vicente-Serrano et al., 2012; Hao & Singh, 2015; Wang et al., 2020). In future work, we aim to enhance CDI by incorporating sector-specific indicators to better assess socio-economic impacts beyond agriculture."

5. Section 3.2: Here, I miss a description of the reasons why the PCA method was chosen to construct the PCA. This is the main innovation of the paper, and should therefore be featured more prominently, also in the introduction. E.g., explain what the added value of the PCA is compared to other techniques to compute a CDI. Why are regression-based approaches not used? (e.g. is it an advantage that the PCA does not have a dependent variable?)

Thank you for this insightful comment. We agree that the reasoning for using PCA to construct the CDI should be made clearer and more prominent, particularly given its central role in our methodology. Accordingly, we have revised the Methods sections to elaborate on this point. The primary reason for selecting PCA is its ability to reduce dimensionality while preserving the maximum possible variance from the original data. Unlike regression-based approaches, PCA does not require a dependent variable, which is particularly advantageous in our context where the aim is to integrate multiple independent agro-climatological indicators into a single composite metric without presupposing a specific impact model.

Furthermore, PCA generates orthogonal (i.e., uncorrelated) components, allowing us to avoid multicollinearity issues that often arise in regression models. This ensures that each input variable contributes uniquely to the CDI. The resulting weights derived from PCA reflect the actual variability and importance of each index within the combined space, making the CDI more representative of spatio-temporal drought conditions across diverse climates. While regression methods could be used if a target impact (e.g., crop yield, water stress) were clearly defined and globally available, our goal was to develop a generalized, impact-sensitive drought indicator suitable for global application and validation against GDIS events.

To address your suggestion, we have now clarified these points in the revised manuscript and added the following text to Section 3.2, line 230-239:

"The PCA method was selected for constructing the CDI due to its ability to extract dominant patterns of variability across multiple input indices without requiring a dependent variable. This makes it particularly suitable for integrative assessments across diverse drought types and geographic regions. Compared to other commonly used weighting methods, such as the Analytic Hierarchy Process (AHP), which relies on expert judgment (Saaty, 1980), or entropy weighting, which uses the diversity of information in data (Mahato et al., 2023), PCA offers an objective, data-driven approach that reduces subjectivity. While regression-based methods have also been explored to link drought indicators with socio-economic impacts (Hao et al., 2014b), they typically require clearly defined response variables and may introduce model-based biases. In contrast, PCA generates uncorrelated components and assigns weights based on explained variance, enhancing reproducibility and generalizability in global-scale assessments."

6. Lines 227-229: What is the total number of observations for the single-based drought indices used in the PCA? Does this number meet the requirements of the no. of observations usually applied in PCA? Please specify.

Thank you for your valuable comment. In our study, PCA was performed separately for each calendar month, using time series data from 21 years (2001–2021). As a result, each monthly PCA was based on 21 observations per variable (SPI, STI, SSMI, and NDVI), giving a subject-to-variable ratio of 5.25:1.

While this sample size is relatively small, it is within the acceptable range for PCA applications, especially given the low number of input variables. According to established guidelines, a minimum subject-to-variable ratio of 5:1 is considered acceptable for stable PCA solutions when the dataset is not highly noisy (Jolliffe, 2002; Gorsuch, 1983). Moreover, the purpose of PCA in our study is to derive objective, data-driven weights rather than to interpret component loadings across multiple dimensions. This limited yet structured approach enabled us to compute monthly-specific weights that reflect seasonal variability in the relationship between drought indicators.

We have revised the manuscript and added an explanation to justify the suitability of the sample size (Section 3.2, Lines 240 - 247).

"In this study, the PCA technique was used to assign monthly weights to the four input indices: SPI, STI, SSMI, and NDVI. PCA is commonly used in environmental and climate studies to extract dominant patterns in multivariate datasets without requiring a dependent variable. In this study, PCA was conducted separately for each calendar month using time series data from 2001 to 2021, resulting in 21 observations per variable. Although the number of observations is relatively modest, it satisfies the commonly accepted subject-to-variable ratio of at least 5:1 for PCA (Jolliffe, 2002; Gorsuch, 1983), especially when the number of variables is low, and the objective is dimensionality reduction. Through PCA, new orthogonal (independent of each other) variables, i.e., P.C.s, were constructed using linear combinations of the original indices without significant loss of information."

7. Lines 258: "…has been widely accepted in previous work." Which previous work? Please provide citations. Please extend this to the other text when you mention previous work without giving references.

Thank you for pointing this out. We agree that such text must include proper referencing. Somehow, this was previously overlooked. In the revised manuscript, all such sentences referring to previous work are now properly cited with the appropriate references. The revised manuscript includes the following modifications at suggested place (section 3.3 line 280);

"Figure 1 illustrates that values below -1 indicate moderately to extremely dry conditions, which have been widely accepted in previous works (McKee et al., 1993; Bayissa et al., 2019a; Kulkarni et al., 2020b)." (section 3.3, line 280)

McKee, T. B., Doesken, N. J., and Kleist, J.: The relationship of drought frequency and duration to time scales, in: Proceedings of the 8th Conference on Applied Climatology, 17–22, Am. Meteorol. Soc., Anaheim, CA, 1993.

Bayissa, Y. A., Tadesse, T., Svoboda, M., Wardlow, B., Poulsen, C., Swigart, J., and Van Andel, S. J.: Developing a satellite-based combined drought indicator to monitor agricultural drought: a case study for Ethiopia, GIsci Remote Sens, 56, 718–748, https://doi.org/10.1080/15481603.2018.1552508, 2019b.

Kulkarni, S. S., Wardlow, B. D., Bayissa, Y. A., Tadesse, T., Svoboda, M. D., and Gedam, S. S.: Developing a remote sensing-based combined drought indicator approach for agricultural drought monitoring over Marathwada, India, *Remote Sens.*, 12, 2091, https://doi.org/10.3390/rs12132091, 2020b.

Similarly, references have been added to line no 575 as follows:

Previous studies, whether regional or global, often relied on single-parameter-based indices for drought monitoring, such as SPI (McKee et al., 1993), NDVI (Ji & Peters, 2003), or soil moisture indices (Liu et al., 2012).

McKee, T. B., Doesken, N. J., and Kleist, J.: The relationship of drought frequency and duration to time scales, Proc. 8th Conf. on Applied Climatology, Anaheim, CA, USA, 17–22 January 1993, American Meteorological Society, Boston, MA, 179–183, 1993.

Ji, L. and Peters, A. J.: Assessing vegetation response to drought in the northern Great Plains using vegetation and drought indices, Remote Sens. Environ., 87, 85–98, https://doi.org/10.1016/S0034-4257(03)00174-3, 2003.

Liu, Y. Y., Parinussa, R. M., Dorigo, W. A., de Jeu, R. A. M., Wagner, W., van Dijk, A. I. J. M., McCabe, M. F., and Evans, J. P.: Developing an improved soil moisture dataset by blending passive and active microwave satellite-based retrievals, Hydrol. Earth Syst. Sci., 15, 425–436, https://doi.org/10.5194/hess-15-425-2011, 2011.

8. Lines 258-265: The thresholds of the drought indices used for detecting the drought impacts listed in the GDIS dataset are very crucial, though the explanation remains too vague (it's a simple process, but I had to read over the section several times to understand this). Please make this process more explicit, e.g. via adding a table. Also, I miss a clear explanation of how the spatial scales between the gridded drought indices and the sub-national GDIS events are matched for the detection of drought impacts (is it counted as drought event if more than half of the pixels in the GDIS area show a deviation below the drought threshold? Or do you first calculate the average of the drought indices across all grid points and then compare it with the thresholds?)

We thank the reviewer for this valuable comment. We agree that greater clarity was needed regarding both the thresholding methodology and the spatial aggregation procedure.

In the revised manuscript, we have now substantially expanded the explanation in this section to clearly describe the consistency assessment process. Specifically:

1. Threshold criteria: For each GDIS drought event (defined by a spatial polygon and temporal range), we extracted the corresponding gridded monthly values of five drought indices: SPI, STI, SSMI, NDVI, and CDI. A given index was considered consistent with the GDIS event if any month within the event's timeframe had a spatially averaged index value within the polygon that was below a set threshold. We used two thresholds in our analysis. A primary threshold of -1, which corresponds to moderate to extreme drought conditions and an alternative threshold of 0, used for sensitivity analysis.

2. Spatial aggregation: To answer the spatial scale difference between gridded indices and the polygonal GDIS data, we computed the mean value of each drought index across all grid cells located within the GDIS polygon for each month. This monthly mean was then compared to the

drought threshold. This approach was chosen over a pixel-count method to ensure consistency and simplicity across different event sizes and spatial resolutions.

Yes, the assessment was based on the average index value across all grid cells within each polygon, which was then compared to the threshold, rather than using a pixel-counting or majority-area approach.

Clarification via a table: We have added table to the appendix (appendix 1), of revised manuscript to summarize the step wise process used in evaluating index consistency with GDIS drought events. This should make the methodology more accessible and easier to follow.

Appendix 1: Step wise procedure for assessing the consistency of gridded drought indices with GDIS drought events

Step	Description
1	For each GDIS event, extract spatial polygon and event time range (referring EM-DAT for event details)
2	Extract monthly gridded index values (SPI, STI, SSI, NDVI, CDI) within polygon
3	Compute monthly spatial average of index values within polygon
4	Check if any month in the event has an average value below threshold
5	If yes, mark that index as consistent with the GDIS event

This revised writeup can be found in section 3.3, from line 269 to line 289 in the revised manuscript. The revised version is as follows.

“The GDIS polygons were overlaid onto the gridded drought index (SPI, STI, SSMI, NDVI, and CDI) layers separately, to extract spatial and temporal raster-based information for each drought event. A total of 2,142 events recorded between 2001 and 2021 were analyzed. Event-specific details such as location and start and end dates were obtained from the GDIS and EM-DAT databases. For each drought event, index values were extracted from the respective raster datasets based on the spatial extent (polygon) and duration of the event. For example, if a GDIS event occurred in Bihar, India, from March to December 2012, the relevant monthly raster values for SPI, STI, SSMI, NDVI, and CDI within the Bihar polygon during that period were extracted.

To align the gridded drought indices with the spatial scale of the GDIS events, we computed the monthly spatial average of each drought index over all grid cells within the corresponding event polygon. This process produced a single time series per index for each event. The resulting geodatabase tables were then analyzed to assess whether the index values were consistent with the

GDIS records. Following previous literature (McKee et al., 1993; Bayissa et al., 2019a; Kulkarni et al., 2020b), a threshold of ≤ -1 was used to define moderate to extreme drought conditions (Figure 1). A drought index was considered consistent with a GDIS event if the average value of the index within the event polygon was ≤ -1 in any month during the event's duration. For instance, if the average STI value within the Bihar polygon fell below -1 in any month between March and December 2012, STI would be considered consistent with that GDIS event. To evaluate sensitivity, a secondary analysis was also conducted using a threshold of < 0. In this case, if any monthly average value of an index was below zero during the event, it was also marked as consistent. This two-threshold approach allowed for both conservative and more inclusive assessments of drought index performance against GDIS events. For clarity, a step wise procedure of thresholding and spatial averaging is presented in appendix 1."

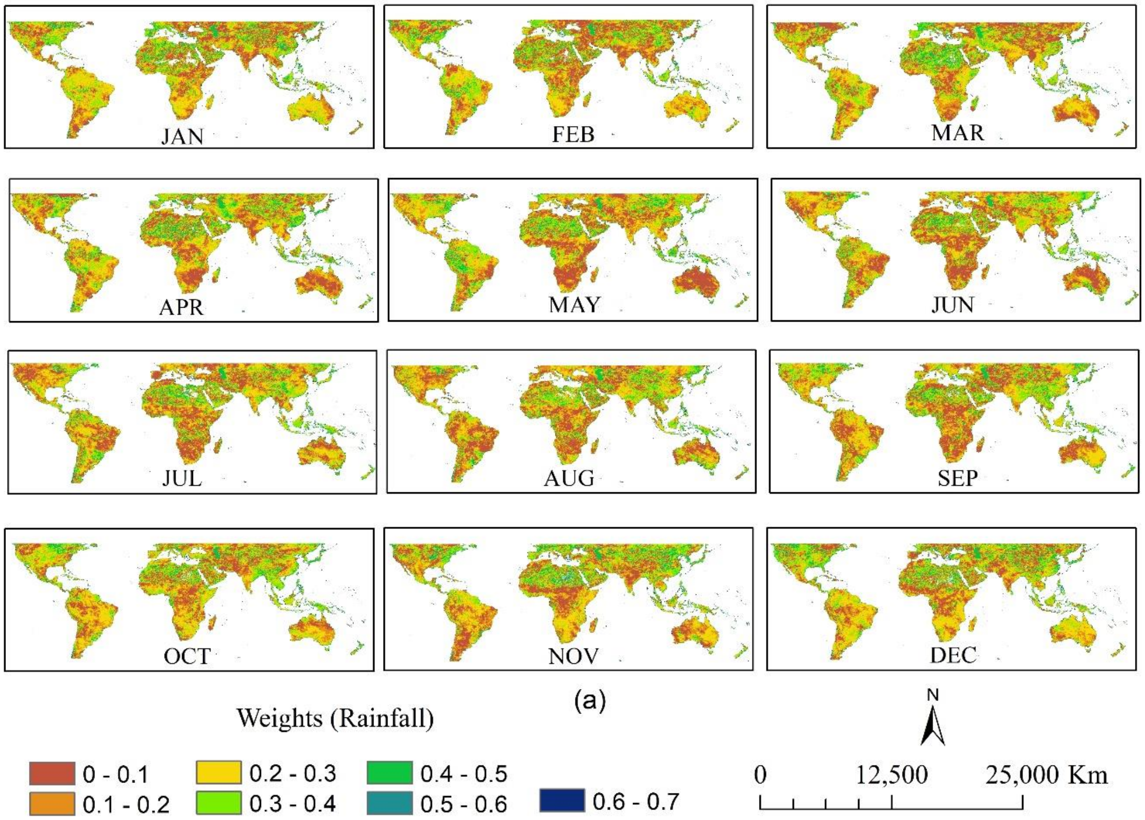
9. Line 327: Please specify why you chose April as the month for displaying the PCA results. Does it represent the yearly average best? How important are intra-annual fluctuations? April is not a typical drought month in the northern or southern hemisphere.

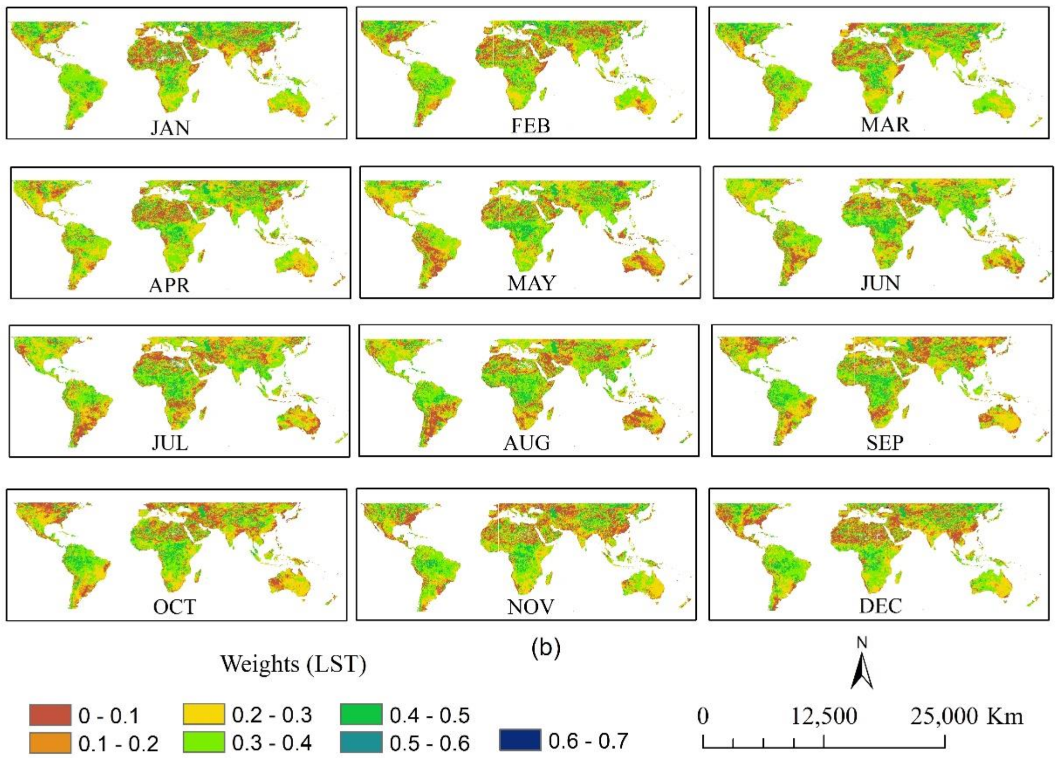
We thank the reviewer for this observation. The PCA analysis was conducted for all twelve months to capture the seasonal variation in drought patterns across different indices. However, due to space constraints in the manuscript, we were unable to include the full set of monthly results.

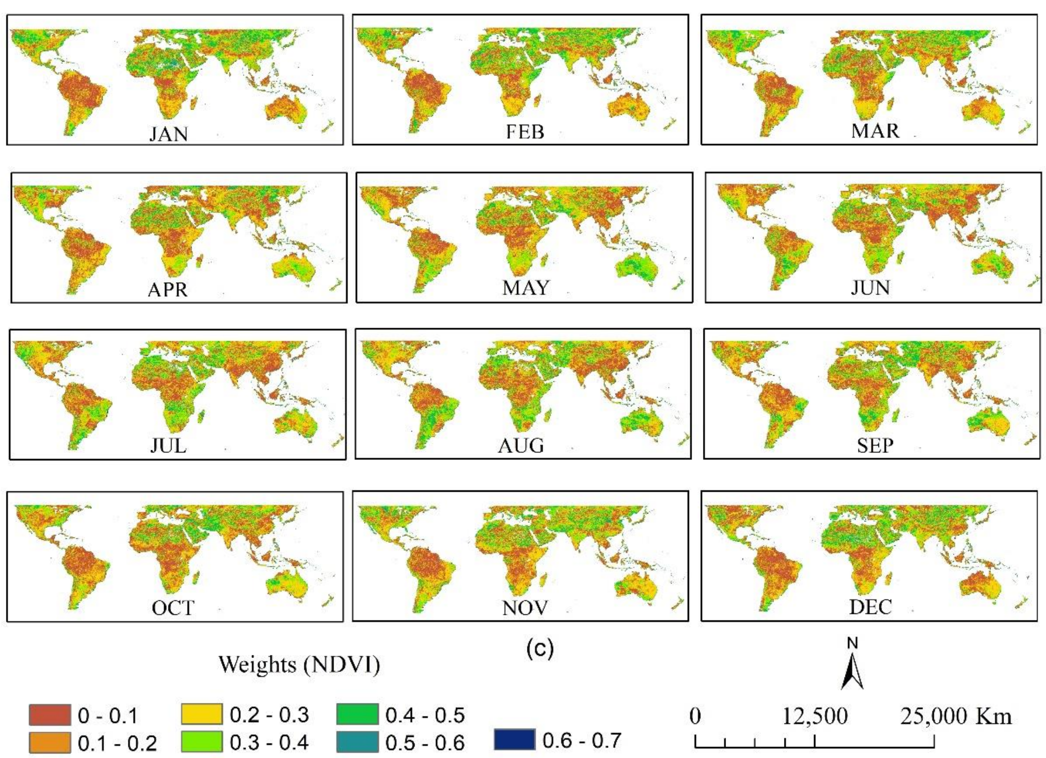
April was selected as a representative example to present in the manuscript as it falls between typical dry and wet seasons in many parts of the world and hence does not overly bias the patterns toward either extreme. While April is not necessarily a peak drought month in either hemisphere, it offers a mid-season picture that helps demonstrate the spatial structure of the PCA components without being overly influenced by strong seasonal extremes.

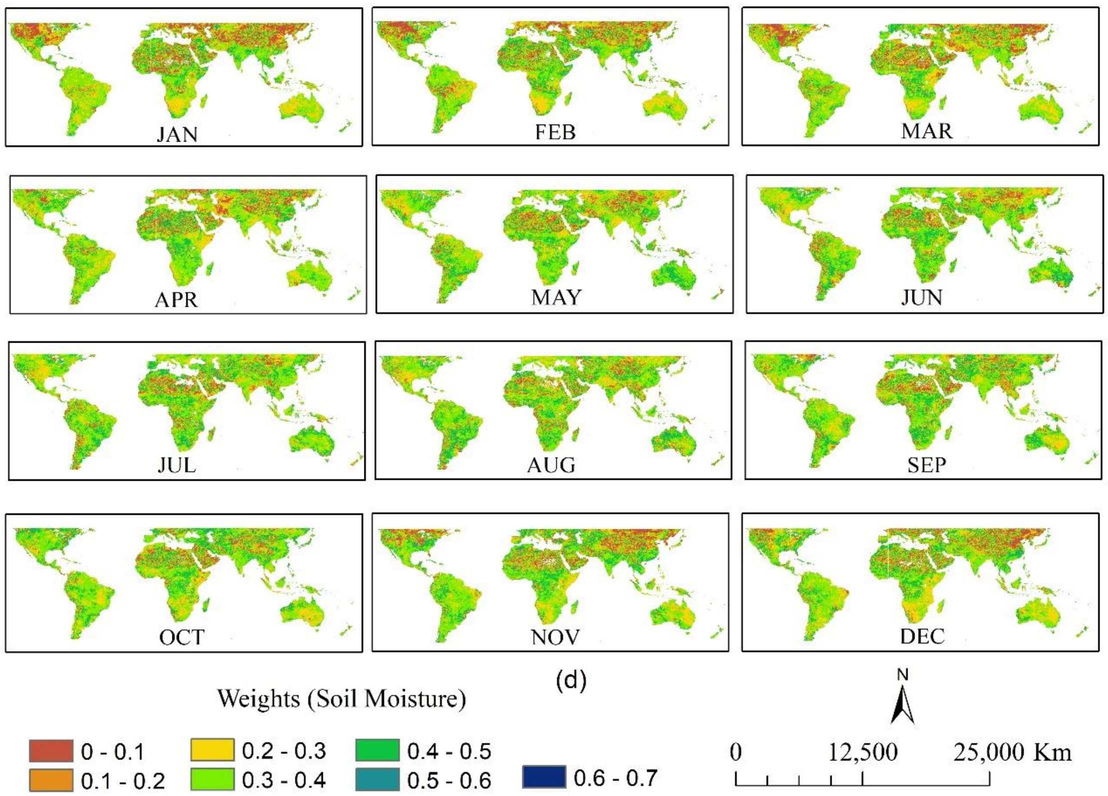
We acknowledge the importance of intra-annual fluctuations and confirm that similar analyses were carried out for each month. The weights computed using PCA for each month and each input variable are provided in the supplementary information of the revised manuscript (Appendix 2). The resulting maps and general interpretation are as follows;

The monthly PCA-derived weight maps show clear seasonal and spatial variation in the importance of each drought input variable. Rainfall (SPI) generally carries higher weights in monsoon-dependent and rain-fed regions during their respective wet seasons, especially in South Asia and sub-Saharan Africa. Soil moisture (SSMI) shows consistently moderate to high weights across temperate and tropical agricultural zones, reflecting its relevance for root-zone drought. NDVI contributes more in heavily vegetated regions like the Amazon, Central Africa, and Southeast Asia during growing seasons, with reduced influence in arid and non-vegetated areas. LST (via TCI) has moderate weights in regions prone to heat stress, particularly during summer in the Northern Hemisphere. Together, these dynamic weights demonstrate CDI's adaptability to seasonal climatic conditions and regional drought sensitivities.


JAN
FEB
MAR
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC
(a)
Weights (Rainfall)
0 - 0.1
0.1 - 0.2
0.2 - 0.3
0.3 - 0.4
0.4 - 0.5
0.5 - 0.6
0.6 - 0.7
N
0
12,500
25,000 Km


JAN
FEB
MAR
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC
Weights (LST)
0 - 0.1
0.1 - 0.2
0.2 - 0.3
0.3 - 0.4
0.4 - 0.5
0.5 - 0.6
0.6 - 0.7
N
0
12,500
25,000 Km
(b)


JAN
FEB
MAR
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC
Weights (NDVI)
0 - 0.1
0.1 - 0.2
0.2 - 0.3
0.3 - 0.4
0.4 - 0.5
0.5 - 0.6
0.6 - 0.7
N
0
12,500
25,000 Km
(c)



Appendix 2. Monthly spatial distribution of PCA-derived weights for rainfall (a), temperature (b), NDVI (c), and soil moisture (d) used in CDI computation. Color scales indicate the relative contribution of each variable to CDI (brown = low weight, green = moderate weight, blue = high weight).

10. Table 2: You show the false-negative (when a GDIS drought event existed, but the drought index did not indicate a drought event) in the table as "not observed". Likewise, what is the rate of false-positive cases (how often did the drought index indicate a drought event not reported in the GDIS?)? You discuss this in the text (lines 390ff), but it would be beneficial for the reader to understand the magnitude of these cases in numbers.

We thank the reviewer for this valuable observation. While Table 2 presents false-negative cases, where GDIS-reported drought events were not detected by the indices, we agree that understanding the magnitude of false-positive cases/instances where an index (such as CDI) indicated drought conditions in locations or periods not reported in GDIS, is equally important.

As mentioned in the manuscript (lines 435), we did observe several such cases visually. For example, the CDI detected drought conditions in South Argentina (2014–15), Namibia (2013), and parts of Europe (2018), which were not captured in GDIS. However, we did not perform a comprehensive quantitative analysis of false positives, primarily due to two key limitations:

1. Incomplete event coverage in GDIS/EM-DAT: Though GDIS gives drought event information, it does not comprehensively cover all real-world drought events, particularly in developing regions with limited reporting infrastructure or where impacts may not meet the threshold for international disaster recording. As a result, a drought detected by an index but missing from GDIS may not necessarily represent a false positive, but rather a real event that went undocumented. This reporting bias makes it challenging to confidently interpret such mismatches as false positives.

2. Lack of defined temporal frames for reverse analysis: Unlike GDIS, which provides explicit event start and end dates, drought indices can show anomalies across various timeframes (monthly, seasonal, annual), making it difficult to define a standard "event" period in the absence of an external reference. Applying a consistent and unbiased reverse framework for identifying false positives is, therefore, not straightforward and risks misclassification.

Given these limitations, we restricted our analysis to a visual identification of potential false-positive instances. However, we fully agree that a quantitative false-positive assessment would be a valuable future direction. With access to more detailed, high-resolution, and timely impact datasets, particularly in underrepresented regions, this could be systematically explored.

We have included this discussion in the revised manuscript (Discussion section, Line 659) as follows:

"While this study focused on false-negative cases using GDIS as a reference, a systematic assessment of false-positive cases remains challenging. This is due not only to the lack of defined temporal frames for reverse analysis but also to the incomplete coverage of drought impacts in GDIS, especially in developing regions where many drought events may go unreported. These limitations could be addressed in future research using more comprehensive and high-resolution impact datasets."

11. Discussion: In the discussion, an important point would be how the CDI could be used/applied for drought impact forecasting and/or policy-making. Could the CDI (computed via PCA) help to improve drought impact forecasting? How does the regionalization of the CDI affect the capacity to be used for that purpose?

Thank you for this insightful comment. We agree that discussing the practical applications of CDI, particularly for drought impact forecasting and policy-making, is important. We have now included a brief discussion in the revised manuscript (Section 5: Discussion, lines 654 - 659) addressing this point. The added text is as follows;

"By integrating multiple indicators, CDI provides a more comprehensive view of drought conditions that is useful for identifying at-risk areas. For example, in regions like East Africa or

Central India, where both rainfall deficits and vegetation stress are common during droughts, CDI captures these multiple dimensions more effectively than single-parameter indices. Its regionalized structure ensures better alignment with local climate dynamics, enhancing its potential utility in forecasting and policy targeting. With adaptation to near-real-time inputs, the CDI framework could support early warning systems and guide proactive measures such as crop insurance triggers or water allocation planning."

12. Lines 570ff: You could additionally mention that text mining is a research field potentially providing alternative impact databases for droughts next to the GDIS.

We thank the reviewer for this valuable suggestion. We agree that text mining and natural language processing (NLP) approaches are emerging as promising tools for generating alternative or supplementary drought impact datasets. These methods have the potential to fill gaps in existing databases such as GDIS and EM-DAT by extracting event-specific impact information from news reports, social media, and institutional records. We have now acknowledged this point in the revised discussion section at lines 679-683, as follows:

"Emerging approaches such as text mining and natural language processing (NLP) offer promising pathways to address this gap by automatically extracting drought impact information from news articles, institutional reports, and social media (Fritz et al., 2019; Sathianarayanan et al., 2024), and could serve as alternative or supplementary impact datasets alongside GDIS and EM-DAT."

13. Line 550: "despite experiencing higher climatic anomalies, developed nations are less likely to be socio-economically affected …". This statement needs to be specified. It needs to become clear that the higher climatic anomalies relate to the local climate, and are not compared in absolute terms. A small anomaly in an already dry climate can provoke much more negative drought impacts compared to a larger anomaly in a wetter climate. Otherwise, this suggests that climate/drought impacts in developed nations are higher than in developing countries, which is not the case.

Thank you for pointing out this. We agree that the original phrasing may have been misleading. Our intention was not to suggest that developed nations experience greater absolute drought impacts, but rather that they may face significant climatic anomalies relative to their own baseline (e.g., unusually dry years), yet are often less socio-economically affected due to higher adaptive capacity and resilience. We have rewritten the sentence in the revised manuscript (Section-discussion, lines 641-643) to clarify our point as follows.

"Although developed nations may experience significant climate anomalies relative to their local climatic norms, they are generally less socio-economically impacted by droughts than developing countries, which tend to be more vulnerable due to limited adaptive capacity."

14. Lines 583-584: "Moreover, there are other methods and techniques that could be used to compute weights in CDI …" Like which methods? Please specify and give a short reason why they could be apt.

We thank the reviewer for this helpful comment. We have revised the manuscript to include specific alternative methods that could be used to compute weights in the CDI. These include entropy weighting, the analytic hierarchy process (AHP), and machine learning-based approaches such as random forest feature importance. Each method offers unique advantages: entropy weighting emphasizes data variability, AHP incorporates expert judgment, and machine learning techniques can capture nonlinear relationships between indicators and observed impacts. These details have been added to the discussion section of the revised manuscript at lines 690-694, as follows:

"Further, other alternative methods such as entropy weighting, the analytic hierarchy process, or machine learning-based feature importance (like random forests) could also be explored to compute weights in CDI, as they may better capture indicator relevance by incorporating data variability, expert knowledge, or nonlinear relationships with observed impacts.

"

Technical corrections:

Line 121: “combine drought indicator” -> correct to “combined”

Thank you. The word 'combine' has been corrected to 'combined' in the revised manuscript (Section 1: Introduction, line 121).

3a: The legend in this panel is missing.

Thank you for pointing out this error. We somehow overlooked it. In the revised manuscript, a legend has been added to Figure 3a. The corrected figure is as follows:

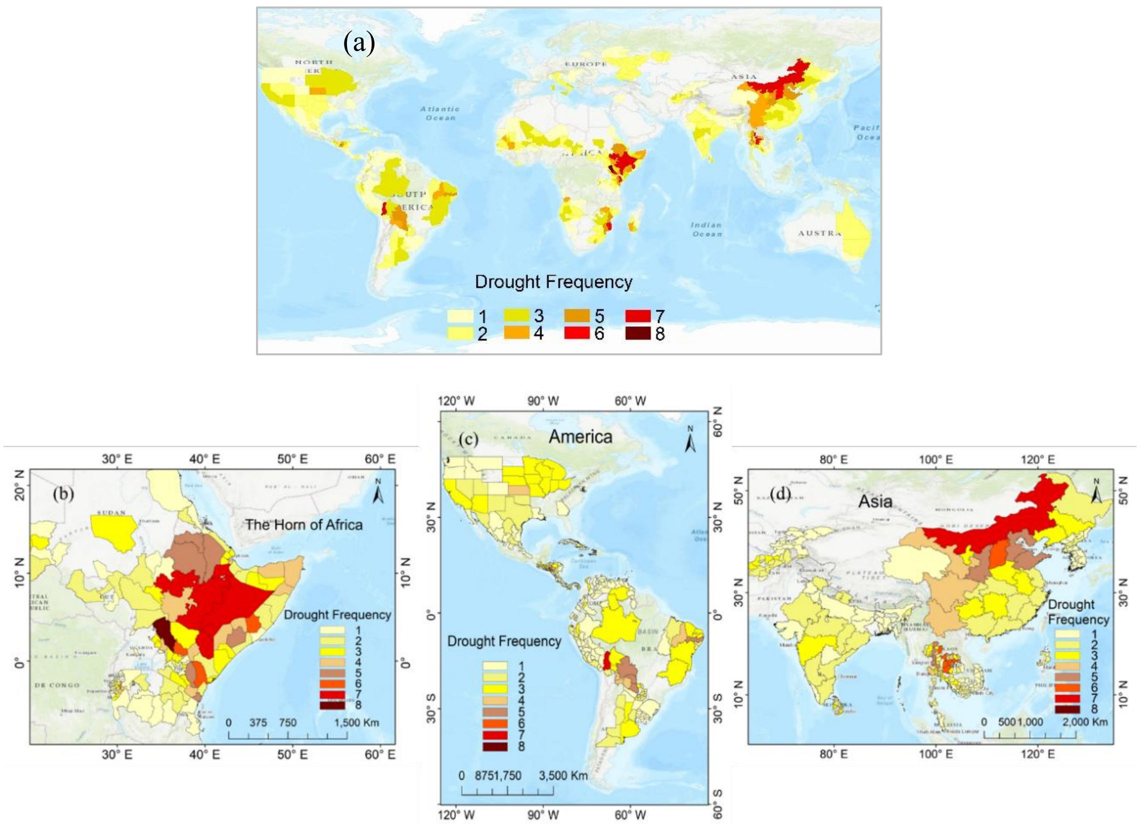


Figure 3. Spatial Distribution of GDIS drought frequencies (a) Global scale (b) East Africa (c) America and (d) Asia. The drought frequencies range from one to eight, represented by shades ranging from light yellow to dark brown, respectively.

9: Second panel: “CDI vs. TCI”, please correct to “CDI vs. STI”

Thank you for the correction. In the revised manuscript, CDI vs TCI has been changed to CDI vs STI. The revised figure is as follows,

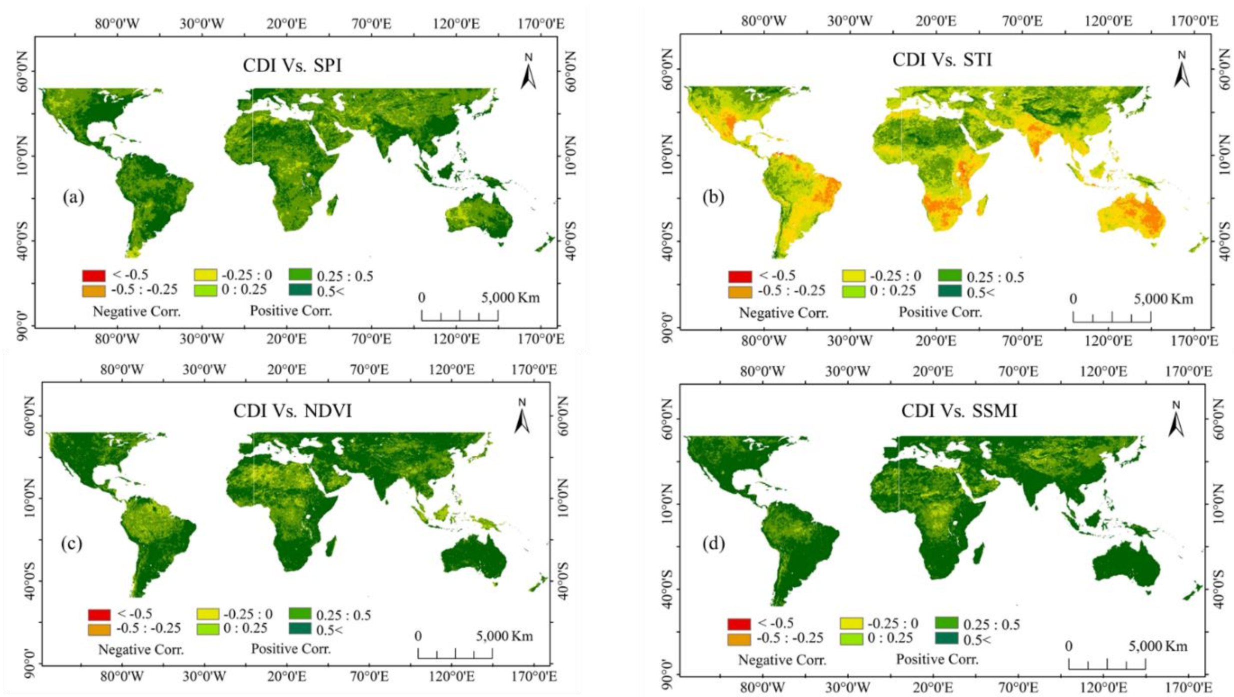
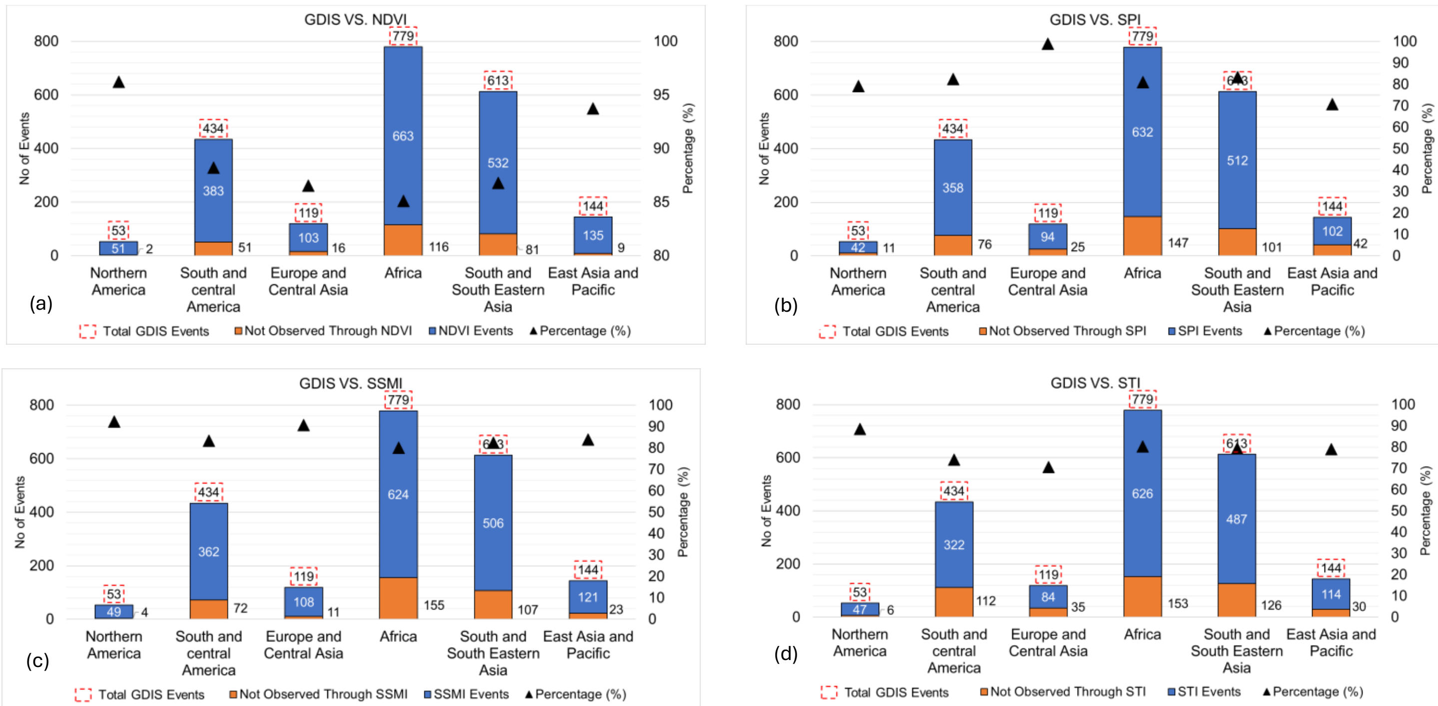


Figure 10. Spatial Correlation Between CDI and Single Input-Based Traditional Indices for a Sample Month (April): (a) CDI vs. SPI, (b) CDI vs. STI, (c) CDI vs. NDVI, and (d) CDI vs. SSMI. Negative correlations are represented in shades from yellow to red, while positive correlations are shown in shades from light green to dark green.

Appendix 2: This figure shows four times the same plot. This should be corrected.

Thank you for pointing out this error. In the revised manuscript, the corrected images have been included. The corrected images are as follows,



Appendix 4: Performance of Traditional Drought Indices in Capturing GDIS Events Across Global Regions: Comparative Assessment of (a) NDVI, (b) SPI, (c) SSMI, and (d) STI

********************* Thank You *********************