Response to Reviewer 2 Comments

MS No.: hess-2024-245

Thanks to the reviewer for reviewing 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

This study analyses the propagation of drought hazards to socio-economic impacts using GDIS data, incorporating multiple drought indices and developing a novel CDI. The results indicate that CDI outperforms other indices, underscoring its utility in risk assessment and prioritization of affected areas. The scope of the study fits well with the journal's theme of the study interactions with human activity, particularly in relation to droughts1.

Although the paper is well-written and structured, it does present some limitations in addressing the socio-economic aspects under study. Additionally, the results provided are insufficient to definitively support the conclusions. Based on the results presented in this paper, it cannot be definitively stated that the CDI index alone can determine the existence of socio-economic drought. After reviewing the manuscript and based on these comments, I recommend that the manuscript be reconsidered after a **major revision** to address the identified shortcomings.

Specific comments

1. The work uses the Global Disaster (GDIS) dataset distributed by SEDAC NASA to identify study areas, which are referred to as GDIS drought events. It is considered that the socio-economic variables used by this database to classify the area as affected should be detailed more precisely, since, as indicated in the discussion, vulnerability depends on the degree of development of the country in which it is located, and therefore the characterisation of the socio-economic variables is an important aspect to consider. The introduction should be expanded to include a detailed description of the socio-economic aspects related to drought and present the state of the art in this field.

Thanks to the reviewer for this insightful comment. As suggested, we have expanded the introduction to provide a clearer overview of the socio-economic impacts of drought and the current state of the art in this field. We have edited the introduction section and new details are added a new paragraph (Lines 86 to 96) that discusses the variation in drought impacts based on development levels, the importance of socio-economic vulnerability, and the limitations of earlier impact datasets. We also explain how the recently developed GDIS dataset addresses these gaps by offering sub-national socio-economic impact data for global analysis.

Revised text (Lines 86 to 96):

"Droughts have significant socio-economic impacts, including crop losses, food insecurity, income reduction, water shortages, and displacement. The severity of these effects varies by region, depending on development level, infrastructure, and adaptive capacity. In high-income areas, systems like irrigation and insurance help reduce impacts, while in low-income regions, even moderate droughts can trigger crises (Brooks et al., 2005; and Pak-Uthai and Faysse, 2018). Recent studies (Panwar and Sen, 2020; and Udmale et al., 2014) highlight the importance of incorporating socio-economic vulnerability into drought assessments. However, the direct link between drought hazards and their socio-economic repercussions remains underexplored, partly due to the limited availability of reliable global impact data. Earlier efforts, such as the U.S. Drought Impact Reporter and the European Drought Impact Report Inventory, provided region-specific insights but lacked global coverage. To address this, the Geocoded Disaster (GDIS) dataset, developed from EM-DAT, offers geocoded disaster locations and detailed sub-national data on affected population, fatalities, and economic losses. By overcoming previous limitations, GDIS enables spatial analysis of drought impacts across diverse socio-economic contexts."

2. This study exclusively utilises climatic variables, such as rainfall and temperature, along with indices like soil moisture and the vegetation index NDVI, without incorporating socio-economic variables. It is important to explain why these variables are not included in characterising drought events.

Thank you for your comment. The main objective of our study is to evaluate the performance of combined versus single drought indicators by comparing them against observed drought event data from the GDIS database. GDIS provides subnational records of actual socio-economic drought-related events, and we use this dataset as an observational benchmark for this study.

In this study, we deliberately did not include socio-economic variables as part of the drought indicators. Our aim is to assess how well agro-climatological indices, such as precipitation, temperature, soil moisture, NDVI, and CDI, can reflect or correspond to real-world drought events rather than attempt to model those events directly. Including socio-economic variables in the indicators would have complicated the evaluation, as it would mean comparing GDIS data against indicators that already include similar information, potentially biasing the results and reducing the objectivity of our assessment.

We acknowledge that some regional studies have incorporated socio-economic data; such as crop prices or agricultural losses, for drought monitoring (e.g., Brown & Funk, 2008; Lobell & Burke, 2010; Wang et al., 2022). However, these approaches are often limited to specific regions and lack the global consistency required for a study of this scale. Our scope is therefore distinct: rather than modeling socio-economic drought events, we evaluate the capacity of agro-climatological indicators alone to serve as reliable proxies for observed drought events globally.

Moreover, for operational drought monitoring and policymaking, particularly at global and subnational scales, consistent, high-resolution, and continuous datasets are essential. Currently available socio-economic datasets often lack such spatial and temporal consistency. Therefore, identifying agro-climatological indicators that closely align with observed drought events can help strengthen early warning systems and support more effective policy decisions, especially in data-scarce regions.

These details have also been included in the revised manuscript (Discussion section, lines 598 to 602) as follows:

"While some regional studies have used socio-economic data such as crop prices or agricultural losses for drought monitoring (e.g., Brown & Funk, 2008; Lobell & Burke, 2010), we exclude such variables to avoid overlapping with the GDIS, which already incorporates socio-economic factors like the number of affected individuals, deaths, and total damage caused by drought. Our focus is on evaluating how well agro-climatological indices, such as CDI, SPI, and NDVI, capture drought events based on climatic and environmental conditions. Additionally, globally consistent socio-economic datasets are often limited, and their availability may vary by region, making agro-climatological based indicators more practical and reliable for large-scale drought monitoring."

3. Given the global scope of this work, only climatological and vegetation predictors are utilised, without considering any socio-economic factors. An important question arises: Are there regions where the proposed index identifies periods of drought that are not recorded as such by the GDIS database? Figure 5 illustrates that certain areas experiencing extreme drought are not within any GDIS polygons. Additionally, it is noteworthy that Figure 5 does not include any European countries.

Thank you for this valuable observation. We fully agree with your point, and indeed, our analysis revealed several instances where the CDI detected drought conditions that were not recorded in the GDIS database. These discrepancies are acknowledged and discussed in detail in Section 4.2 (lines 435-443) of the manuscript as follows:

“CDI detected severe drought events in South Argentina during 2014–15, Namibia in 2013, and parts of Europe in 2018, which were not reflected in GDIS event records. These instances highlight that not all agro-climatic droughts lead to recorded socio-economic impacts, especially in regions with strong adaptation and mitigation capacities. Practices such as advanced irrigation, drought-resistant crop varieties, or effective early warning systems may help manage the agricultural and societal impacts of climatic stress, thereby reducing the likelihood of such events being recorded in GDIS. It is also important to note that GDIS does not comprehensively capture all real-world drought events, particularly in regions with limited reporting mechanisms or institutional capacity. As a result, some drought events, especially in low-income or remote areas may go undocumented despite having significant local impacts.”

Regarding the absence of European countries in Figure 5, we would like to clarify that this figure presents a sample representation of selected drought events globally and does not suggest that Europe did not experience droughts. In fact, CDI-detected events in Europe, such as the 2018 drought are discussed in the manuscript, and for further clarity, a sample map of European events is attached herewith (Figure 1). However, we also wish to highlight that, in comparison to other regions, Europe and Australia show fewer drought-related entries in the GDIS database. This supports our broader observation that developed regions (e.g., Europe, USA, Australia) tend to report fewer socio-economic drought events possibly due to stronger infrastructure, better preparedness, and adaptive capacity. This contrast further underscores the importance of evaluating agro-climatic indicators like CDI, which can identify stress conditions even when no disaster impacts are formally reported, especially in data-scarce or impact-resilient regions.

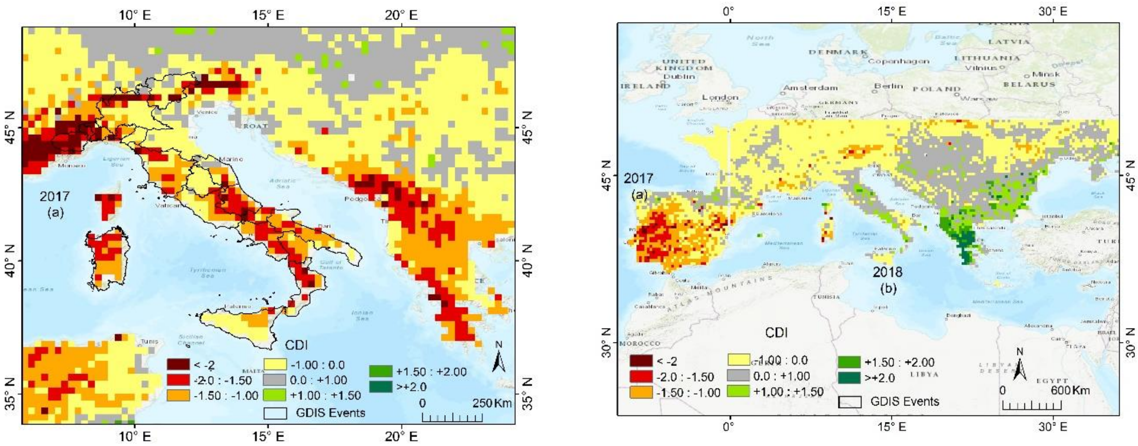


Figure 1. Comparison of CDI Detected Droughts and GDIS Events Over Europe: (a) 2017 Drought Over Italy with Strong CDI–GDIS Overlap, and (b) 2018 Drought Over Spain and Surrounding Regions Detected by CDI but Not Captured by GDIS.

4. In section 2.3 it is indicated that soil moisture is obtained using a weighting for each of the strata; however, it is not detailed how it is obtained, and the way in which this is done should be explained, since it is one of the variables used to characterise the combined drought index, and as shown in the weights in Figure 4, this variable is quite important in the determination of this combined factor.

Thank you for your comment. We appreciate the opportunity to clarify the method used to derive the soil moisture input for CDI, given its importance in the analysis. We used the ERA5-Land soil moisture dataset (European Centre for Medium-Range Weather Forecasts, 2023), obtained from the Copernicus Climate Data Store, covering the period 2001 to 2021 with a spatial resolution of 0.1° × 0.1° and monthly temporal resolution. This dataset provides soil moisture values across four depth levels: (Layer 1: 0–7 cm, Layer 2: 7–28 cm, Layer 3: 28–100 cm, Layer 4: 100–289 cm). For our analysis, we used the first three layers (0–100 cm) to represent root-zone soil moisture, which is widely mentioned in the literature as critical for agricultural drought monitoring (e.g., Bolten et al., 2010; Entekhabi et al., 2010; Sehgal et al., 2017). Root-zone moisture reflects the water available for vegetation and crops and is particularly relevant for assessing impacts visible through NDVI and other surface stress indicators. To obtain a single representative soil moisture value for the top 1 m, we calculated a weighted average of the three layers based on their respective thicknesses. This approach ensures that deeper layers, which store more moisture and contribute more significantly to long-term water availability, are proportionally represented, while still capturing the sensitivity of upper layers to short-term dry conditions.

We excluded the fourth layer (100–289 cm) from the analysis, as it extends well beyond typical rooting depths and is less responsive to seasonal surface drought, especially in relation to vegetation stress and agricultural impacts. The resulting root-zone soil moisture value was then standardized (e.g., using z-scores) and integrated into the CDI framework along with other drought-relevant indicators.

This explanation has been added in the revised manuscript under Section 2.3, lines 151-159, as follows:

"We used the ERA5 Land soil moisture dataset (European Centre for Medium-Range Weather Forecasts, 2023) acquired from the Copernicus Climate Data Store for the study period from 2001 to 2021. The monthly data products, with a spatial resolution of 0.1 x 0.1 degrees, were used for the study. The soil moisture datasets were available for different soil depth levels: first (0–7 cm), second (7–28 cm), third (28–100 cm), and fourth (100–289 cm). For our analysis, we used the first three layers (0–100 cm) to represent root-zone soil moisture, which is widely recognized in the literature (Bolten et al., 2010; Sawada, 2018; Sehgal et al., 2017) as critical for agricultural drought monitoring. To obtain a single representative value for soil moisture in the top 1 m, we employed a weighted averaging method using the respective thicknesses of the first three layers. The resulting weighted root-zone soil moisture layer was then standardized (e.g., using z-scores) and integrated into the CDI framework along with other drought-relevant indicators."

5. Section 2.5 states that '*we assumed January as the starting month and December as the end month of the respective event, and further analysis was carried out*'. Taking into account that the hydrological year in many databases is from October to September, It Would be important to know what percentage of the data used assume an unknown period, and to analyse the sensitivity of the results obtained to a possible alteration of the hydrological year.

Thank you for your insightful comment. In our dataset of 2,142 drought events derived from the GDIS database, 143 events (~6.7%) did not have a specified start month. For these events, we assumed January (month 1) as the default starting month to ensure their inclusion in the analysis.

We acknowledge that the hydrological year varies across regions. However, given that the number of events with missing start months represents a small proportion of the total dataset (<7%), we believe that this assumption has a minimal impact on the overall results. The number of such events and their percentage have now been explicitly mentioned in the revised manuscript under Section 2.5, lines 183-185 as:

"In some cases (143 events out of 2142 ~6.7%), due to the unavailability of monthly details in EM-DAT, we assumed January as the starting month and December as the end month of the respective event, and further analysis was carried out."

6. Regarding the results section, the results are presented in absolute terms by quantifying the number of detected and undetected events, which makes them difficult to understand. The quantification of the accuracy of the proposed methodology should be done using specific metrics obtained from a confusion matrix, detailing: Accuracy, Precision, recall, specificity, F1-score, AUC, etc. This will allow the discussion section to be completed by comparing similar metrics from previous work.

Thank you for your valuable feedback. In response to your comment regarding the evaluation of our methodology using specific performance metrics, we have now included a detailed assessment of 'recall' (a key metric from the confusion matrix) across multiple scenarios. As shown in the new figure (below figure 2), we evaluated all five drought indices under four time windows: (a) Actual Event Period (AEP), (b) One Month Prior + AEP, (c) Two Months Prior + AEP, and (d) Three Months Prior + AEP.

We chose recall as a primary metric in this comparison because of its importance in drought detection, capturing as many actual drought events as possible is critical for early warning systems and risk mitigation. As such, higher recall values indicate better detection capability.

Across windows all the time, CDI consistently outperforms or is on par with other indices, especially when short droughts are excluded (i.e., longer droughts of ≥2 months). Example: In panel (a), CDI has the highest recall (0.94) when considering longer drought events. In panels (b), (c), and (d), CDI maintains recall values of 0.96–0.97, outperforming or matching the best-performing indices in each respective window. This shows the robustness and sensitivity of CDI in capturing drought events over both short- and long-term windows.

We agree that NDVI and SSMI show relatively high recall in specific cases (panel b, One Month Prior + AEP); such behavior is expected due to their sensitivity to vegetation stress and soil moisture. However, CDI demonstrates the most robust and consistent recall overall, across all scenarios and time windows, highlighting its superior ability to detect drought events under different conditions.

We also acknowledge the importance of evaluating performance through a complete confusion matrix, including false positives, false negatives, and derived metrics such as precision, specificity, and F1-score. However, this requires a complete and unbiased ground-truth dataset. As discussed in our response to a previous comment, GDIS does not capture all real-world drought events due to limitations in reporting infrastructure, particularly in data-scarce regions. As a result, metrics that rely on the assumption of full event coverage (such as precision or specificity) may be unreliable in this context. Therefore, we focused on recall as the most informative and robust metric for evaluating detection performance in a globally heterogeneous impact reporting system like GDIS.

However, your suggestion to explore additional performance metrics derived from the full confusion matrix is highly valuable and could be an excellent direction for future extensions of this study, particularly when more comprehensive ground-truth data becomes available.

This analysis and the newly generated figure have been added to the revised manuscript as follows (Section 4.3, lines 481–487):

"For comparative analysis of drought detection performance, recall serves as a crucial metric, as it quantifies the ability of each index to correctly identify actual drought events. High recall is especially important in early warning systems, where missing events can lead to unmitigated impacts. As illustrated in Appendix G, the CDI index consistently outperforms others across all time windows, particularly for events lasting ≥2 months, where it achieves recall values between 0.94 and 0.97, demonstrating robust and reliable drought detection capability. For a more comprehensive understanding of detection performance, additional metrics derived from a full confusion matrix, such as precision, specificity, and F1-score, could provide further insights and represent a promising direction for future work."

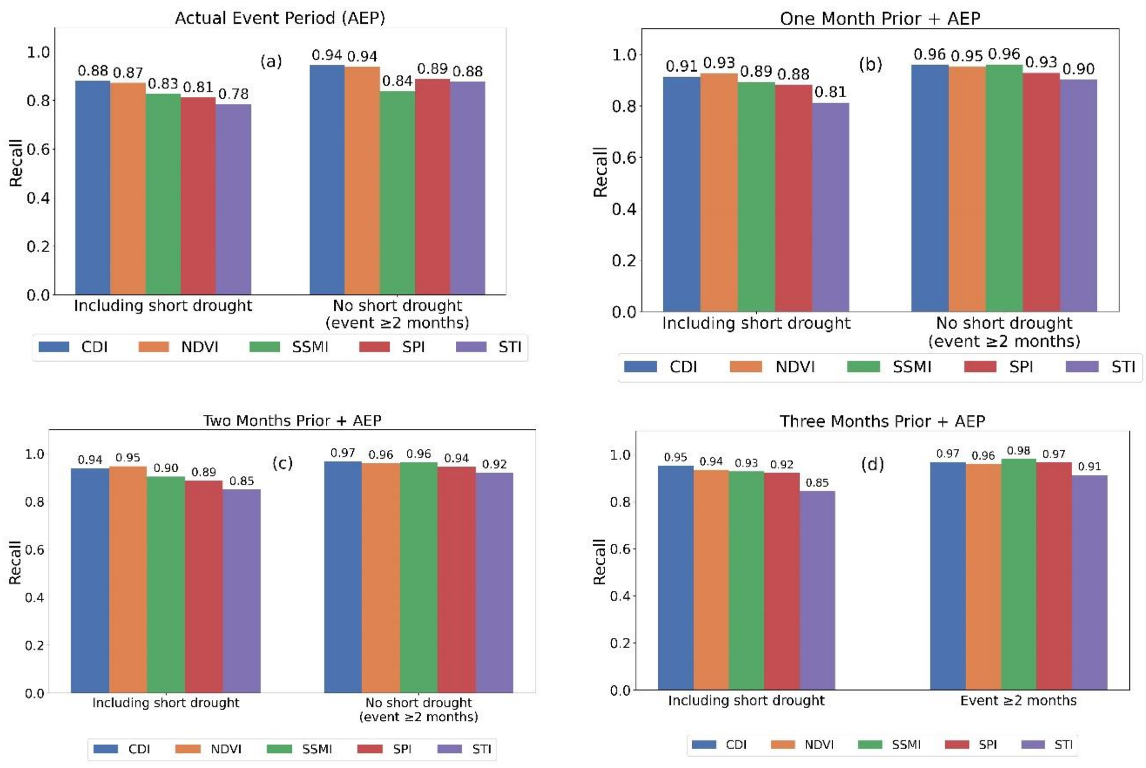


Figure 2: Comparative recall performance of five drought indices (CDI, NDVI, SSMI, SPI, and STI) across different time windows and event durations.

7. From the visual analysis of Figure 7, it cannot be concluded that the combined index is clearly better than the individual indices, as indicated in line 525 as the results represented in that figure the combined index performs almost as well as the NDVI and in some cases slightly worse.

Thank you for pointing out this. We acknowledge that in some individual cases (as shown in Figure 7), other indices, such as NDVI or SSMI, show slightly higher event counts than CDI. This variation is expected because, NDVI and SSMI are highly sensitive to vegetation and soil moisture changes, which may capture localized drought signatures more prominently in certain periods.

However, our intention was not to claim that CDI outperforms all indices in every individual instance. Rather, the overall trend across different time windows and event durations demonstrates that CDI consistently maintains high performance, combining information from multiple indicators. This makes it more robust and generalizable across diverse drought conditions. We have revised the language in line 525 to better reflect this revised interpretation, in the revised manuscript (section 5: discussion, lines 612-615) as follows,

"The comparative analysis between the CDI and other individual parameter-based indices suggests that CDI offers a strong overall capability for detecting GDIS events, showing robust performance across time windows and a closer association with socio-economic impacts."

8. The analysis of the accuracy of the different indices could be completed with information on the socio-economic characteristics of each region as well as the typology of land cover in the region analysed, the accuracy metrics according to these variables in order to be able to conclude in a quantifiable way under which conditions one index performs better than another.

We thank the reviewer for the valuable suggestion. In response, now we have extended the analysis to include a zonal-level evaluation of index performance across the four major Köppen climate zones (Arid, Temperate, Tropical, and Cold) (Figure 9 in revised manuscript) and major land cover classes (Appendix H in the revised manuscript). To carry out the first analysis, initially GDIS polygons were spatially intersected with the respective climate zone shapefiles. However, due to topological limitations when working with two polygon layers, a direct one-to-one assignment was not always feasible. To address this, a 50% spatial overlap criterion was applied to assign each GDIS event to a climate zone. This ensured meaningful spatial classification and avoided ambiguous assignments. Applying this rule resulted in 2161 zonally attributed GDIS events, a slight increase from the original 2142 events due to partial overlaps at climate zone boundaries.

For each of these events, the start and end dates were used to extract corresponding values from multiple drought indices (CDI, SPI, SSMI, NDVI, STI). A threshold of -1 was used to determine whether an index detected a drought event. Based on this, index-wise detection counts were computed for each zone.

This analysis helps quantify the accuracy of each index under distinct climatological conditions, shedding light on their behavior under different topographies and regional drought patterns. The results are presented in the figure below. This figure shows that while individual indices perform well under certain climate regimes (e.g., SSMI and NDVI in arid zones), the CDI consistently demonstrates high association with GDIS events across all zones, suggesting its robustness and general applicability. This figure and analysis have also been included in the revised manuscript as Figure 9.

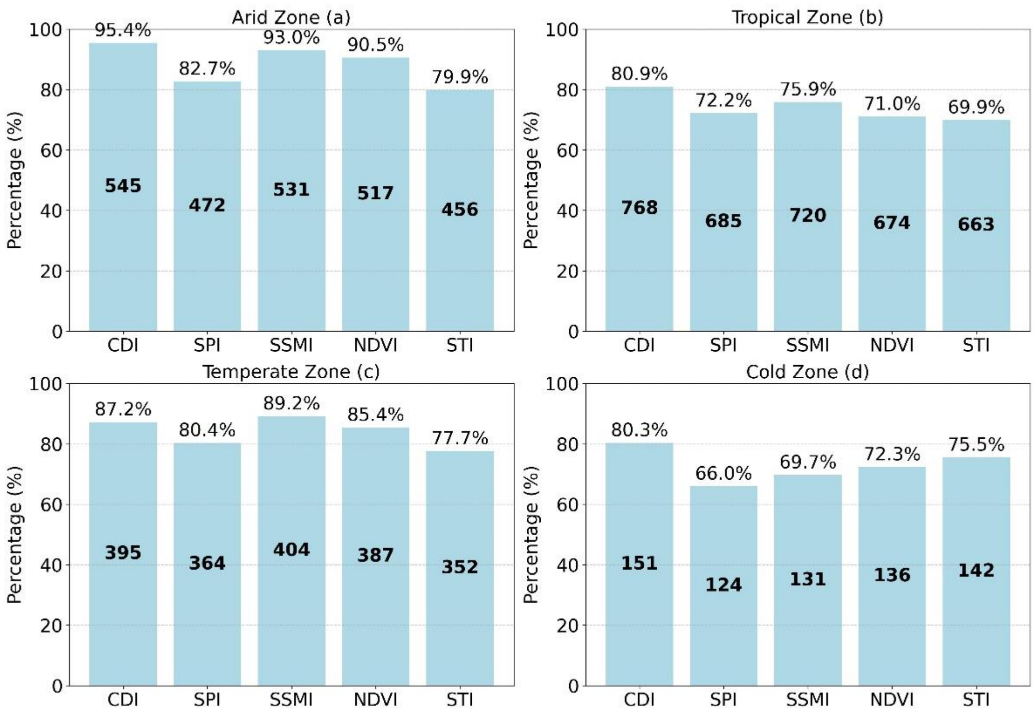
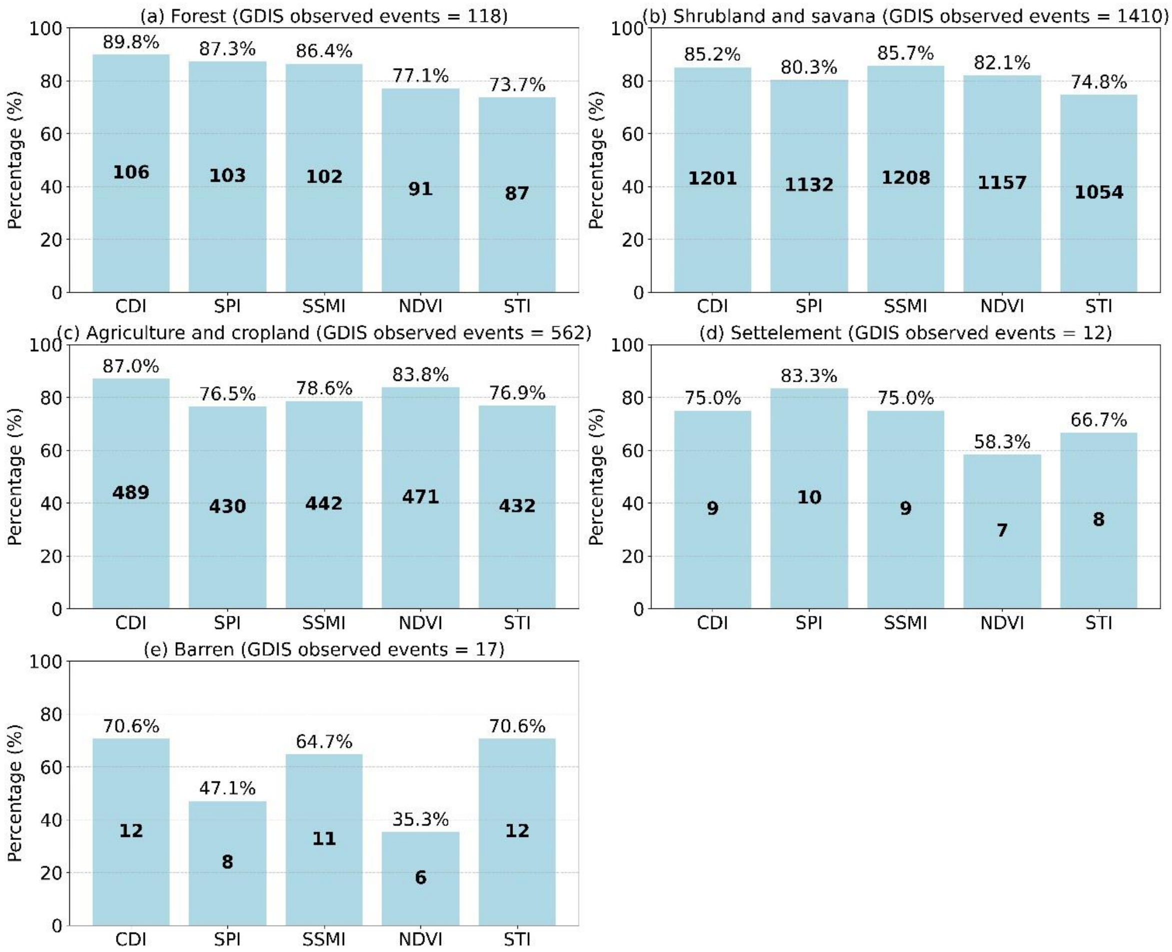


Figure 9. Zone-wise accuracy of drought indices (CDI, SPI, SSMI, NDVI, STI) in detecting GDIS events across four Köppen climate zones: Arid, Tropical, Temperate, and Cold. The bar heights represent the percentage of GDIS events accurately captured by each index (threshold = -1), and the numbers inside the bars indicate the absolute number of consistent detections. The total number of GDIS events considered per zone is: Arid – 571, Tropical – 949, Temperate – 453, Cold – 188 (Total = 2161).

Similarly, we also performed a zonal validation of drought index performance across major land cover classes: Forest, Shrubland and Savanna, Agriculture and Cropland, Settlement, and Barren lands, based on the MODIS land cover dataset. The original MODIS classification includes 17 land cover types, which we reclassified into five broader categories for this analysis. For each GDIS event, the dominant land cover type was identified, resulting in the following distribution: Forest – 118, Shrubland and Savanna – 1410, Agriculture and Cropland – 562, Settlement – 12, and Barren – 17. Using a threshold criterion of -1, we evaluated each index's ability to detect these events. The results indicate that CDI consistently outperformed individual indices across all land cover types, reinforcing its robustness in capturing multi-dimensional drought signals, even under heterogeneous surface conditions. Notably, SSMI slightly outperformed CDI in the Shrubland and Savanna class, and SPI showed better detection in Settlement areas. However, given the variability and sparsity of certain land cover types, such deviations are expected. The detailed results are as follows and also included in the revised manuscript in Appendix H.



Appendix H: Land cover–wise accuracy of drought indices (CDI, SPI, SSMI, NDVI, STI) in detecting GDIS events across five major land cover classes (Forest, Shrubland and Savanna, Agriculture and Cropland, Settlement, and Barren) based on MODIS land cover data. The bar heights represent the percentage of GDIS events accurately captured, while values inside the bars indicate the absolute number of consistent detections. The total number of GDIS events considered per land cover class is Forest – 118, Shrubland and Savanna – 1410, Agriculture and Cropland – 562, Settlement – 12, Barren – 17.

The detailed analysis on climate zones (figure 9) and land cover classes (appendix H) is mentioned in section 4.3 lines 525 to 549 as follows:

"Figure 8 represents the zonal validation results for drought index performance across four climate zones (Arid, Tropical, Temperate, and Cold) based on Köppen's climate classification (threshold criterion: -1). The figure highlights how different indices perform differently under varying climatic conditions, while the CDI demonstrates consistently high detection accuracy across all zones. In the Arid zone (a), CDI detected 95.4% of GDIS events (the highest among all indices), while SSMI and NDVI also performed well with 93.0% and 90.5%, respectively. This can be attributed to the high sensitivity of NDVI and SSMI to vegetation and soil moisture stress, which are obvious under arid conditions. However, in the Cold zone (d), individual index performance dropped noticeably, with SPI detecting only 66.0% of events, whereas CDI still maintained 80.3% detection. Similarly, in the Temperate zone (c), both CDI and SSMI showed strong association with GDIS at 87.2% and 89.2%, respectively, indicating that some indices may be better suited for certain climate types. In contrast, Tropical zone (b) showed relatively lower detection percentages for all indices, with CDI still leading at 80.9%. SSMI performance in tropical and cold zones was lower, possibly due to dense vegetation cover and higher variability in surface moisture, which can limit the accuracy of soil moisture retrievals. These results emphasize that while individual indices can perform well in specific climate zones, their performance is not consistent across all zones. CDI, by integrating multiple indicators, offers more universally reliable detection, making it better suited for broader applications in drought monitoring across diverse climatic regions.

Similarly, we performed a zonal validation of drought index performance across major land cover classes, Forest, Shrubland and Savanna, Agriculture and Cropland, Settlement, and Barren lands, based on MODIS land cover data. As shown in Appendix H, the results indicate that CDI consistently outperformed individual indices across all land cover types in detecting GDIS events. This reinforces the robustness of CDI in capturing multi-dimensional drought signals, even across heterogeneous land surface conditions."

9. From line 470 to Figure 9, the purpose of testing the correlation between the combined index and the indices should be clarified. Considering that the combined index has been obtained from a principal component analysis of these variables, it is logical that it is correlated with the different parameters according to the weighting weights, it should be clarified what the purpose of this analysis is.

Thank you for this observation. We agree that, since the CDI is derived through PCA, a certain level of correlation with its input indices is expected due to the weighting structure. However, the purpose of this correlation analysis was threefold:

- To complement the spatially varying PCA weight maps by showing actual spatial alignment between CDI and its components over time. While the PCA weight maps reflect each component's contribution during index construction, they do not directly represent how consistently each index aligns with CDI behavior in practice.

- To account for the temporal variability of PCA weights. Since the PCA is performed monthly, the weights assigned to each component index vary over time. This makes it difficult to interpret long-term or spatial relationships between CDI and its components just by examining the weights. The correlation maps provide a more interpretable, time-integrated view of these relationships.

- To support the interpretation of CDI behavior across different climatic regions by identifying where specific indices (e.g., precipitation, NDVI, or SSMI) are more or less aligned with the composite CDI signal. This helps explain regional variations in CDI performance.

For example, Figure 9 shows that SSMI consistently has a strong positive correlation with CDI across most regions, emphasizing the dominant and stable role of soil moisture in shaping the CDI signal globally.

To clearly convey the purpose of this analysis, we have included an explanatory statement in the revised manuscript (Section 4.3, lines 550–551):

"To better understand the spatial behavior of the CDI, a correlation analysis was performed (Figure 9) to examine how consistently each input index aligns with the composite signal across regions."

10. As mentioned above, there are conclusions that are not justified by the results presented. Lines 593 to 595, The following is stated: ‘*This novel index surpassed the performance of four commonly used single-parameter-based traditional indices, demonstrating superior accuracy in identifying GDIS droughts and effectively representing their socio- economic impacts*’. However, as mentioned above, this conclusion is not supported by the information and results presented in this work.

Thank you for pointing this out. We acknowledge that the original phrasing may have overstated the conclusion beyond what the presented results directly support. In the revised manuscript (lines 713–715), we have reworded the statement to more accurately reflect the findings. The revised text is as follows:

"The comparative analysis indicates that the proposed index performs consistently well across different drought scenarios and offers a more integrated representation of drought patterns, showing strong association with observed GDIS events and potential links to socio-economic impacts."

This revised conclusion is based on the recall-based performance metrics (Appendix G), correlation patterns (Figure 9), and visual comparisons that demonstrate CDI’s robustness across space and time. We believe this updated wording better aligns with the scope and evidence presented in the manuscript.

11. Lines 599 to 600: The following is stated: *‘CDI-derived drought clusters exhibit a statistically significant representation of GDIS drought events (indicative of socio-economic impacts), with 95% of the GDIS events successfully 600 identified using the CDI’*. However, to support this assertion, it is necessary to consider the full set of metrics from the confusion matrix. While the index may identify GDIS-catalogued drought events, it could also detect other drought events that do not necessarily have socio-economic effects. Based on the results presented in this paper, it cannot be conclusively stated that the CDI index alone can determine the existence of socio-economic drought.

Thank you for this important clarification. We fully agree that detecting GDIS events alone does not confirm that the CDI can directly identify socio-economic droughts, as it may also detect events without documented impacts. Our intent was not to claim a deterministic relationship between CDI and socio-economic droughts, but rather to highlight the strong association between CDI-identified drought clusters and reported GDIS events.

To address this, we have revised the statement in the revised manuscript (section 6, lines

720-723) to better reflect the scope of our findings. The updated sentence is as follows:

"CDI-derived drought clusters show strong spatial and temporal association with GDIS-reported drought events, with approximately 95% of GDIS events successfully identified using the CDI. This suggests that the index effectively captures drought conditions that frequently align with documented socio-economic impacts."

A full confusion matrix requires a reliable identification of false negatives, that is, actual socio-economic drought events that were not captured by GDIS. As discussed in earlier responses, this is not currently feasible due to the incomplete coverage of real-world drought impacts in GDIS. Therefore, our analysis is limited to comparing CDI signals against known, documented events and does not aim to establish CDI as a comprehensive socio-economic drought detector. Since there is no globally consistent and exhaustive database of socio-economic drought impacts, we cannot objectively determine which CDI-identified events are true false negatives or simply unreported impacts, making such analysis infeasible at this stage. However, developing such a reference dataset and enabling robust false negative analysis would be a valuable direction for future research.

Technical corrections

1. It should be clarified whether the ranges in Figure 3 correspond to the classification set out in Figure 1, and if so, the nomenclature should be homogenised.

Thank you for this observation. We clarify that the ranges in Figure 3 do not correspond to the classification presented in Figure 1. Figure 1 displays the CDI classification scheme, where values range from negative to positive, representing a range from wet to drier drought conditions. On the other hand, Figure 3 presents the frequency of drought events, using a color gradient from light yellow to dark red to indicate low to high drought frequency. While some of the color tones may appear visually similar between the two figures, they represent entirely different variables and scales. We have revised the figure caption for Figure 3 (now Figure 2 in the revised manuscript) to clarify this distinction. The revised caption is as follows,

"Figure 2. 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 from light yellow (low frequency) to dark brown (high frequency). Note: The color scheme used here is distinct from the CDI classification shown in Figure 1 and represents event frequency, not drought intensity."

2. Figure 7 has very low resolution, however, as it is proposed to replace the figure with a display of the results in terms of the metrics of the confusion matrix, I understand that this figure will be replaced in its new format.

Thank you for pointing this out. In the revised manuscript, Figure 7 (now Figure 6 in the revised manuscript) has been replaced with a higher-resolution image to improve visual clarity. Additionally, as suggested, a confusion matrix–based recall analysis has been added as a new figure in Appendix G to provide a more quantitative comparison of index performance.

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