Carta aos revisores 3

Dear Editor,

We resubmit our revised manuscript entitled "The dynamics of spatio-temporal droughts in Northeast Brazil" for consideration in *Hydrology and Earth System Sciences*. We sincerely thank you and the referees for the thoughtful and constructive feedback. Following Round 3, we conducted a comprehensive revision focused on (i) clarifying methodological choices and terminology, (ii) strengthening the conceptual positioning relative to prior spatio-temporal and cumulative-curve approaches, and (iii) improving the readability and interpretability of key figures and results.

Below we provide a concise overview of the main changes implemented.

1) Clearer framing and positioning in the Introduction

- We rewrote the introductory storyline to explicitly acknowledge the broad literature on drought event characteristics (e.g., duration, deficit volume/severity, intensity and related descriptors) and the established development of spatio-temporal drought tracking/clustering methods.
- We refined our statement of the specific gap addressed by this study: an interpretable intra-event evolution diagnostic (three-curve framework), a typology of intra-event trajectories, and probabilistic phase transitions.

2) Clarification of terminology ("3D" vs. spatio-temporal) and what is fundamentally new

- We clarified that we use "3D" as shorthand for event-based tracking in longitude–latitude–time, consistent with terminology in parts of the tracking literature, while acknowledging that the broader concept is widely referred to as spatio-temporal drought analysis.
- We made explicit that the novelty of our work lies not in event tracking per se, but in the three-curve intra-event framework, typology assignment, and transition-probability interpretation layered on top of tracking.

3) Methods strengthened for transparency and reproducibility

- We explicitly described typology assignment as visual template matching (two authors independently classified events; disagreements resolved by consensus).
- We added a short conceptual comparison of our 2D+overlap tracking approach versus "fully 3D" connectivity-based clustering approaches, to situate our methodological choices.
- We clarified the implications of the overlap threshold (1.6%) for event fragmentation/merging, event duration, and potential impacts on typology outcomes.

4) Expanded comparison with cumulative-curve approaches (SAD/NATA, Banfi et al.)

- We added targeted text in the Introduction/Discussion highlighting how NATA-based approaches summarize events via cumulative standardized curves, whereas our framework explicitly couples state, integral (growth), and derivative (dynamic) signals to reveal turning points and support typology and phase-transition inference.

5) Improved figure clarity and interpretability of results

- We revised figure captions to remove ambiguity (including the meaning of white/grey background areas in figures showing clusters).
- We added a "How to read" guide directly before the transition-matrix figure, including an explicit numerical example, and refined the narrative interpretation to be row-wise (conditional) rather than suggestive of global ranking.

In addition to these substantive revisions, we performed a careful editorial pass to remove typos, improve consistency in terminology, and eliminate potentially absolute wording that could cause avoidable minor revisions.

We hope the revised manuscript now addresses all remaining concerns and is suitable for publication. Thank you again for your time and consideration.

Sincerely,

João Dehon Pontes Filho
(on behalf of all co-authors)

REFEREE #1

Dear Referee #1,

Thank you for your careful review and for noting that the manuscript has advanced considerably. We appreciate your remaining requests for minor improvements focused on clarity and methodological precision. Below we respond point-by-point and provide the final text added to the manuscript.

Report #1

Comment 1:

"It would be helpful to clarify whether the classification of drought typologies is performed automatically or through visual assessment. I couldn't find it."

Response

We thank the reviewer for highlighting this point. We agree that the manuscript did not state this procedure explicitly in the Methods section, which may have made it difficult to locate. We added an explicit Methods statement in Section 2.4 clarifying that typology assignment is performed via visual matching against theoretical templates, with independent double-coding and consensus resolution. We also kept the sentence in the Results indicating that the classifications were "visually assigned" (Section 3.4), but it now functions as a reaffirmation of a clearly defined Methods procedure rather than the first mention of the approach.

Manuscript change (Methods):

"Typology assignment was performed through visual template-matching. For each drought event, we compared the observed State Curve shape (for affected area and severity) against the four theoretical evolution templates (Types I–IV), based on the relative prominence and sequencing of expansion, persistence, and contraction phases. Two authors independently assigned each event (or event segment) to the best-matching typology; disagreements were resolved through joint review and consensus. When a single event exhibited clearly distinct evolution patterns over its lifetime, the event was segmented into successive sub-periods and each segment was classified separately."

Comment 2:

"Authors could briefly expand the conceptual comparison with recent studies that use cumulative curve approaches (for example, Banfi et al. 2024) to better highlight the distinct contribution of your proposal."

Response:

Thank you for this suggestion. We agree that a clearer conceptual comparison with cumulative-curve approaches helps sharpen the distinct contribution of our framework. We therefore expanded the manuscript in two places (Introduction and Discussion) to explicitly contrast our three-curve model with the NATA-based approach recently used by Chen et al. (2023) and Banfi et al. (2024). We added a short conceptual comparison (Introduction/Discussion) clarifying that NATA is a cumulative standardized curve representation, whereas our framework explicitly combines state + integral (growth) + derivative (dynamic), which (i) makes turning points explicit and (ii) supports phase-based typology and probabilistic phase transitions.

In addition, the following paragraphs were added.

Manuscript change (Introduction)

"Recent cumulative-curve approaches, such as the Normalized Area–Time Accumulation (NATA) framework (Chen et al., 2023; Banfi et al., 2024), provide an elegant standardization to compare drought events of different durations by expressing their evolution in terms of normalized area and time and, in some applications, fitting the resulting curve with an analytical function to delimit broad stages (e.g., early growing, consolidation, exhaustion). This is useful for retrospective synthesis and inter-event comparison. However, because these approaches primarily summarize each event through a single standardized cumulative trajectory, phase turning points are typically obtained indirectly (e.g., from properties of a fitted curve) and are not naturally expressed as a coupled set of state, integral, and derivative descriptors. Moreover, NATA-based typologies remain largely descriptive and do not explicitly quantify the likelihood of switching among drought phases. These limitations motivate our three-curve framework, which explicitly separates the instantaneous drought state, its cumulative evolution, and its rate of change, enabling transparent identification of turning points and a probabilistic characterization of phase transitions."

Manuscript change (Discussion)

"Our framework is complementary to NATA-based analyses (Chen et al., 2023; Banfi et al., 2024) but differs in what it makes explicit for interpretation and decision support. In NATA, the event is summarized by a standardized accumulation curve and phases can be delineated from analytical properties of a fitted function, which provides a compact representation of temporal evolution. Here, instead, we treat drought evolution as a coupled signal system: the State Curve describes the instantaneous condition of a chosen drought characteristic, the Growth Curve accumulates its trajectory over the event lifespan, and the Dynamic Curve (first derivative) reveals turning points and phase boundaries directly from changes in the rate of evolution. This decomposition is not tied to a single cumulative template and can be applied consistently to different drought characteristics (e.g., affected area and severity), allowing comparisons of how multiple variables evolve within the same event. Importantly, by pairing phase identification with a transition matrix, we move beyond descriptive staging and provide a probabilistic view of drought dynamics (i.e., the likelihood of remaining in or switching between expansion,

persistence, and contraction), which is particularly relevant for proactive planning and early warning."

Comment 3:

"Although the use of the 1.6 percent threshold for spatial overlap is now better justified, adding one sentence on how this parameter may influence event identification,and most importantly, events' characteristics such as duration, a characteristic that potentially changes the typological classification, because a longer duration produces alonger total drought area".

Response

Thank you for this suggestion. We agree that the manuscript should explicitly state how the overlap threshold can influence event tracking. We added a short clarification in the tracking description (Methods) explaining that the overlap criterion controls whether consecutive monthly drought patches are linked into the same event or split into separate events. Specifically, a **more stringent (larger) overlap threshold** tends to produce **shorter and more fragmented** events (more splits), whereas a **more permissive (smaller) threshold** tends to yield **longer and more merged** events (more joins). Because this choice affects event duration and cumulative quantities (e.g., accumulated affected area and severity), it can also influence the relative prominence of expansion/persistence/contraction phases and, consequently, the resulting typology classification.

Manuscript change (Methods)

"The overlap threshold controls whether consecutive monthly drought patches are linked into a single event or split into multiple events. A larger (more stringent) overlap requirement generally yields shorter, more fragmented events, whereas a smaller (more permissive) threshold promotes longer, more merged events; by affecting event duration and cumulative metrics, this choice can alter the relative prominence of phases and thus potentially influence typology assignment."

Comment 4:

"Include a short conceptual comparison of the construction of drought events from the 2D approach following the overlapping areas threshold approach with the fully 3Dapproach, for instance Diaz et al. (2023)."

Response:

We thank the referee for this helpful suggestion. We agree that our event construction corresponds to a tracking-by-linkage strategy that starts from 2D clusters and then builds 3D events through temporal connections, and that this should be explicitly distinguished from fully 3D clustering approaches that operate directly in the space–time domain.

In our workflow, drought objects are first extracted at each time step as 2D contiguous clusters using an 8-neighbour rule and a minimum area filter (Step 3). Then, in Step 4, these 2D clusters are linked across consecutive months when an areal overlap threshold is satisfied, producing a 3D event as a sequence of connected 2D "slices" through time. This overlap-based linkage also allows explicit split/merge handling: clusters can merge into a single event ID when they coalesce in the future, and (in our implementation) split fragments can retain the same initial ID, preserving simultaneous evolutions within one event ID.

By contrast, the "fully 3D" family of methods described by Diaz and co-authors can treat the drought field as a single space–time cube where drought cells are connected not only in the 2D plane but also across time, e.g., by extending spatial connectivity to the time domain (26 nearest neighbours forming a cube in space–time) and then identifying 3D connected components. In that case, the 3D drought objects emerge directly from a single 3D connectivity definition rather than from a pairwise overlap criterion between consecutive 2D clusters.

Following the referee's request, we added a short conceptual comparison in the Methods (Step 4) to clarify this distinction and to state why we adopted the 2D+overlap tracking approach (transparent control of continuity via overlap and explicit management of splits/merges), while acknowledging that fully 3D connectivity-based clustering is a valid alternative when a direct 3D connectivity definition is preferred.

Manuscript change (Methods):

*"In our framework, 3D drought events are constructed by first identifying 2D contiguous drought clusters at each time step (8-neighbour connectivity) and then linking clusters across consecutive months using an areal overlap criterion. This 'tracking-by-overlap' approach builds a 3D event as a time-ordered sequence of connected 2D slices, enabling explicit split/merge handling through the linkage rules. In contrast, other 3D clustering approaches define connectivity directly in the space–time domain (*26 nearest neighbours forming a cube in space–time) *and identify 3D connected components without an explicit overlap-based linkage stage. We adopted the 2D+overlap tracking for transparency and control over temporal continuity while acknowledging that 3D connectivity-based clustering represents a valid alternative when a direct space–time connectivity definition is preferred."*

REFEREE #2

Dear Referee #2,

Thank you for your detailed and constructive review. We appreciate your emphasis on accurate positioning relative to decades of spatio-temporal drought research and on improving interpretability of the presentation. We have enhanced substantially the manuscript quality based in your five general comments and your detailed line-by-line comments. Below we respond point-by-point and provide the final text added or revised.

Comment 1:

"This study is novel in its analysis of drought evolution typologies using three curve models and drought transformation using a transition matrix. These approaches are complementary to previous studies that have analyzed drought characteristics. However, the way the authors build the storyline in the introduction is somewhat limited to SAD and NATA. There are many studies that analyze spatio-temporal drought characteristics, such as drought severity, duration, frequency, deficit volume, etc (e.g., Fleigh et al., 2006; Yang et al., 2018; Sutanto and Van Lanen, 2020; Hisdal et al., 2024). I suggest that the authors revise the introduction by incorporating these studies, including SAD and NATA, while clearly emphasizing that existing analyses of drought characteristics generally do not define drought evolution typologies and transformation."

Response:

We agree that the Introduction should more clearly acknowledge the extensive literature on drought-event characterisation and avoid wording that could be interpreted as implying that spatio-temporal drought analysis is novel. We therefore revised Section 1 (Introduction) to (i) explicitly recognise that drought events have long been quantified through attributes such as duration, deficit volume/severity, minimum intensity and related metrics, which underpin both univariate and multivariate drought risk/frequency assessments (e.g.Fleig et al., 2006; Sutanto and Van Lanen, 2020; Yang et al., 2018; Shiau, 2006; Pontes Filho et al., 2020), and (ii) acknowledge that event-based tracking/clustering in longitude–latitude–time is an established line of spatio-temporal drought research. We also clarified terminology by stating that we use "3D" as shorthand for event-based tracking in longitude–latitude–time, following terminology used in previous tracking/clustering studies, while recognising that the broader concept is widely referred to as spatio-temporal drought analysis.

Finally, we strengthened the statement of our distinct contribution: the novelty does not lie in the "3D" label itself, but in the three-curve intra-event phase diagnostic, the typology of evolution, and the probabilistic phase-transition matrix, which provide a structured and interpretable complement to both aggregate event descriptors and tracking-based descriptions.

Manuscript change (Introduction):

"Alongside these developments, drought events have long been characterized through attributes such as duration, deficit volume (severity), minimum intensity and related metrics, typically derived from event definitions based on thresholds or index time series (e.g., Fleig et al., 2006; Sutanto and Van Lanen, 2020; Yang et al., 2018). These descriptors underpin a broad body of drought frequency and risk-assessment studies, including multivariate formulations that explicitly account for dependence between key characteristics (e.g., duration and severity) rather than treating them in isolation (e.g.,(Pontes Filho et al., 2020; Shiau, 2006b).

While essential to quantify magnitude and recurrence, such summaries inevitably compress each event into a small set of aggregate descriptors and therefore provide limited diagnostic information on how an event unfolds internally (e.g., when it shifts from rapid expansion to persistence or contraction). Complementary to these event summaries, spatio-temporal drought research has developed event-based tracking and clustering approaches that follow drought footprints in longitude–latitude–time, enabling the analysis of moving, merging and splitting clusters and the derivation of trajectory-related diagnostics.

Here, we use "3D" as shorthand for this event-based tracking in longitude–latitude–time, following the terminology adopted in previous clustering/tracking studies, while acknowledging that the broader concept is widely referred to as spatio-temporal drought analysis. Building on this established literature, our focus is not on introducing spatio-temporal tracking per se, but on addressing a remaining gap: providing an interpretable intra-event phase diagnostic (State, Growth and Dynamic curves), a typology of intra-event evolution, and probabilistic phase-transition information that can complement both aggregate descriptors and tracking-based descriptions."

Comment 2:

"I am wondering what the difference is between the so-called 3D drought assessment and conventional spatial-temporal drought assessment based on thresholds. In the 3D framework, the first D is about temporal drought event identification, the second D is about spatial clustering of drought event, and the last D is about spatio-temporal tracking. However, all of these 3D analyses have already been performed in many studies, although they are typically referred to simply as spatio-temporal analysis rather than 3D analyses.

The authors also state that traditional drought assessment only provides snapshots of specific areas under drought (Page 14), which is not correct. Spatio-temporal analyses of drought have been introduced decades ago, but again they were not framed using a 3D terminology. I am not against the use of the term 3D assessment but I would appreciate clarification on what is fundamentally new compared to conventional assessment."

Response

Thank you for this important clarification request. We fully agree that the three elements we refer to as "3D" (temporal identification, spatial clustering, and spatio-temporal tracking) have been addressed in the literature for many years under the broader umbrella of spatio-temporal drought analysis, and we did not intend to claim otherwise. We have revised the manuscript to make this explicit and to avoid wording that could be read as implying novelty of spatio-temporal analysis itself.

Our intention in introducing the "3D" shorthand is to distinguish, within the wide set of approaches that incorporate space, between two conceptually different families that are often conflated in drought monitoring narratives:

- Fixed-boundary spatial treatments (e.g., regionalization via Thiessen polygons, PCA, k-means, or reporting drought status for administratively or hydrologically predefined units), which incorporate spatial variability but implicitly assume stable spatial partitions over time; and
- Object-based space–time event tracking, where drought is represented as contiguous clusters that can move, expand/contract, merge, and split in longitude–latitude–time, without being constrained by predefined physical boundaries. In practice, such object-based event tracking has become substantially more widespread with modern gridded products and computationally efficient tracking algorithms that explicitly operate in the space–time domain.

We also agree with the reviewer that the statement "traditional drought assessment only provides snapshots" was too strong and not universally correct. We have replaced it with a more accurate formulation: while spatio-temporal analyses exist, many operational products and many summary communications still rely on time-slice maps and fixed-area reporting, and these can obscure how individual events internally evolve through time.

Finally, we clarify that what is fundamentally new in our study is not the use of space–time tracking per se, but the interpretable intra-event evolution framework built on top of event tracking: the three-curve decomposition (State, Growth/integral, Dynamic/derivative) that makes turning points and phase boundaries explicit, the evolution typologies derived from these diagnostics, and the transition matrix that provides a probabilistic description of phase switching. We have revised the Introduction and Methods to reflect this positioning more clearly and to ensure that "3D" is presented as a terminology choice for an event-based space–time workflow rather than as a claim of novelty over decades of spatio-temporal drought research.

Manuscript change (Introduction):

“However, these approaches represent spatial variability through fixed regional partitions (administrative or statistically derived), which can obscure the continuous and shifting spatial footprint of drought as it propagates. In contrast, more recent object-based space–time event approaches treat drought as evolving clusters in longitude–latitude–time, without requiring predefined boundaries.”

Manuscript change (Results):

“While spatio-temporal drought analyses have been developed for decades, many operational monitoring products and many synthesis communications still present drought conditions as time-slice maps and/or fixed-boundary regionalization; our framework complements these approaches by providing interpretable intra-event evolution diagnostics, typologies, and probabilistic phase transitions.”

Comment 3:

“I am curious about the concept of drought evolution typologies. Could the authors clarify whether this typology is based on existing literature or newly proposed in this study, and please provide the relevant references if applicable. I am also wondering whether flash droughts can be categorized within one of these typologies. If so, which category would flash droughts fall into?”

Response:

We thank the reviewer for this important request for clarification. We agree that the manuscript should state more explicitly the status of the four typologies. In the revised version, we clarify that the four typologies (Types I–IV) are proposed in this study as conceptual archetypes to classify intra-event evolution trajectories derived from the three-curve framework; they are not intended to reproduce a single “standard” typology already established in the literature. They are designed to provide an interpretable vocabulary for how drought events evolve through expansion, persistence, and contraction phases, and to support the subsequent transition-matrix analysis of phase switching.

Regarding flash drought, we also agree that it is important not to overstate the applicability of our present setup. Because our analyses are based on SPI-12, our event definition targets seasonal-to-interannual drought variability and is not designed to detect flash drought, which is typically framed as rapid onset over shorter time scales. We now state this explicitly in the manuscript. Nevertheless, the proposed framework is general and can be applied to shorter-scale indicators (e.g., SPI-1/SPI-3 or daily-scale SPEI/soil-moisture anomalies). Under such short time scales, a flash drought would likely manifest as a trajectory dominated by rapid expansion/onset, which would map preferentially to our “rapid expansion” archetypes (Types II/III/IV), depending on whether the event subsequently exhibits a persistent plateau or transitions quickly into contraction. We added a short sentence to make this linkage clear and to connect with the reviewer's point about SPI-1/SPI-3.

Manuscript changes (Methods):

Added text (Methods, Section 2.4):

"The four typologies (Types I–IV) are introduced in this study as conceptual archetypes for classifying intra-event evolution trajectories derived from the three-curve framework. They are not intended as a consolidation of a single pre-existing typology from the literature, but as an interpretable set of templates describing how drought events can evolve through expansion, persistence, and contraction."

Added text (Discussion):

"Because the present application is based on SPI-12, our event definition targets seasonal-to-interannual drought variability and is not designed to detect flash drought, which is commonly defined by rapid onset at shorter time scales. However, the proposed framework is general and can be applied to shorter-scale indicators (e.g., SPI-1/SPI-3 or daily-scale SPEI/soil-moisture anomalies). Under such settings, flash droughts would be expected to produce trajectories with rapid expansion/onset, which would preferentially map to the rapid-expansion archetypes (Types II/III/IV), depending on whether a persistent phase develops or the event transitions rapidly into contraction. We therefore do not interpret the SPI-12 events analysed here as flash droughts; the reference above is provided only to indicate how the framework could be transferred to shorter time scales."

Comment 4:

"The explanation of Figure 7 is unclear, and I find it difficult to follow the description of the findings based on this Figure. For example, the authors state that for severity, the transition probabilities are observed at the expansion and contraction stages shifting toward persistence. However, when I looked at expansion and contraction, I see the probability of 0.13 or 0.04 and when I see persistence, it is 0.73. This raises the question of whether the matrix is meant to be interpreted from the lowest to the highest value. If so, this interpretation is not clearly explained, and it is also unclear why persistence value is always having the highest probability. I suggest that the authors provide clearer guidance on how to read and interpret this transition matrix and better explain the key findings shown in Figure 7."

Response:

We thank the reviewer for pointing out that the transition matrix in Figure 7 needs a more guided explanation. We agree that, although the manuscript already states that diagonal values represent phase persistence and off-diagonal values represent phase switching, it did not provide an explicit “how to read” instruction that makes the interpretation unambiguous. Also, it was noted that Figure 7 is actually Figure 8, and this mistake was corrected.

To address this, we added a short “How to read Figure 8” paragraph immediately before the figure, clarifying that: rows correspond to the phase at time *t*, columns correspond to the phase at time *t+1*, and each row sums to 1 (i.e., conditional transition probabilities).

We also clarified that the matrix is not meant to be interpreted from “lowest to highest” values globally; instead, it should be read row-wise, as probabilities conditional on the current phase. Finally, we included a concise numerical example (using values already displayed in the matrix) to illustrate how to interpret one row without ambiguity, e.g., if an event is in Persistence at month *t*, the matrix indicates a 0.73 probability of remaining in Persistence at *t+1* and 0.13 probabilities of transitioning to Expansion or Contraction.

We also slightly revised the accompanying text that describes the main pattern (“shifting toward persistence”) to make clear that the key message is about which destination phase is most likely conditional on being in Expansion or Contraction, rather than suggesting an ordering from low to high values. These edits do not change any results; they only improve readability and reduce interpretation ambiguity.

Manuscript changes (Results):

“To further investigate the temporal dynamics of drought evolution, a transition matrix was developed, consolidating all drought events analyzed in this study and its results are presented in Figure 8. Rows indicate the drought phase at time step t *(previous time step), and columns indicate the phase at time step* $\mathrm{t}+1$ *(next time step). Therefore, each cell represents a conditional probability* $P(phase_{t+1} = j \mid phase_t = i)$, *and each row sums to 1. Values along the main diagonal represent the probability of remaining in the same phase from t to* $\mathrm{t}+1$, *whereas off-diagonal values represent the probability of transitioning to a different phase. The matrix should be interpreted row-wise (conditional on the current phase), rather than as a ranking from the lowest to the highest value across the entire matrix. Higher values along the diagonal suggest a strong persistence of each phase, whereas higher off-diagonal values indicate frequent transitions between phases. Example: For severity, if an event is in Persistence at month* t, *the matrix indicates a 0.73 probability of remaining in Persistence at* $\mathrm{t}+1$, *and 0.13 probabilities of transitioning to Expansion or to Contraction. Higher probabilities for Persistence reflect the fact that, at a monthly time step, drought characteristics often evolve with temporal inertia, so persistence between consecutive months is frequent.*

When analyzing Figure 8, we see that the two variables behave differently in terms of how their dynamics evolve over the course of the event.

On the one hand, the severity dominant pattern is that when the event is in Expansion or Contraction, the most likely transition in the next time step is to Persistence, rather than a direct switch to the opposite phase or to keep in the same phase. For instance, we can see this pattern by looking at the first row in the Transition Matrix. Once the event is in Contraction phase in time t*, its probability to keep in Contracion in time* $t+1$ *is lower than to go to Persistence (*$P = 0.45$ *and* 0.51*, respectively. The same pattern is presented when looking at the Expansion row. The probability to keep in Expansion is lower than to go to Persistence next time (*$P = 0.4$ *and* 0.46*, respectively). This indicates a tendency for severity dynamics to change its phase with high frequency, with rapid Contraction or Expansion, returning to Persistence often.*

On the other hand, for the affected area, the dynamics are such that if the drought is in Contraction at time t*, it is more likely to remain contracting at time* $t+1$ *(*$P = 0.6$*) than to move to another phase such as Persistence or Expansion (*$P = 0.37$ *and* 0.03*, respectively). The same is true when the drought is Persistence or Expansion.*

Despite this difference in the dynamic's behavior, both variables presented one single dominant behavior: if the drought event is in Persistence in time t*, it tends to remain in Persistence in time* $t+1$*, presenting* 0.73 *and* 0.78 *probability. This result, which shows a strong persistence component in drought events in both variables, is consistent with the results presented in the typological assessment found in this study, since type II droughts, which were the most frequently found in the region, occur mostly in the persistence phase."*

Comment 5:

"The method section, especially sections 2.2-2.5 can be enhanced with more references. Moreover, the study findings can be better confronted with previous studies in the discussion section."

Response:

We agree that the Methods (Sections 2.2–2.5) and the Discussion benefit from stronger anchoring in the existing literature. In the revised manuscript, we enhanced both components in two ways:

1. Additional references in Methods (Sections 2.2–2.5). We introduced references at the exact points where methodological components

previously defined in the literature are used in our workflow, rather than describing these elements without attribution. Specifically, we added citations when applying: (i) SPI-related choices and time-scale interpretation; (ii) threshold-based event identification and event characterization; (iii) spatial clustering/object-based delineation of contiguous drought patches; (iv) spatio-temporal event tracking procedures (including overlap-based linkage and the conceptual relation to fully 3D connectivity-based approaches);

2. Stronger confrontation of findings with previous studies in the Discussion. We revised the Discussion to more explicitly compare our results with prior work on (i) cumulative-curve/event-summary approaches (e.g., SAD/NATA-type representations) and what additional information is gained by the three-curve (State–Growth–Dynamic) diagnostic; (ii) spatio-temporal tracking/clustering studies and how our event handling (coexisting events, merging/splitting behavior, and tracking choices) relates to those frameworks; and (iii) interpretation of phase persistence and phase switching in light of known drought "inertia" and time-scale dependence (SPI-12 vs shorter aggregation periods). This expanded confrontation clarifies what is consistent with earlier findings, where our results diverge, and what new interpretability is provided by the typology + transition-probability framework.

Overall, these edits do not alter the results; they improve the scholarly grounding of the Methods and provide a more explicit and balanced interpretation of the findings relative to previous studies.

Main Line by line comments:

Comment:

"Figure 3. If I am analyzing SPi-12 using gridded precipitation data, then I

can also get Figure 3. Why do I need to follow the algorithm proposed by Diaz et al. (2019) and Herrera-Estrada et al. (2017)? Also in Figure 3, could the authors explain what do white and grey colors refer to? Also in Figure 5."

Response: *Thank you for this comment. We agree that gridded SPI-12 fields allow one to map drought conditions at each time step, but Figure 3 is not intended to show a generic SPI-12 snapshot. Instead, it illustrates the outcome of an object-based space–time event definition: at each month, contiguous drought cells are clustered, and then clusters are tracked across consecutive months to form distinct drought events (with event IDs) that may move, expand/contract, merge, or remain separate. This step is essential to (i) consistently delineate the spatial footprint of each event through time, (ii) keep simultaneous events separated rather than implicitly mixing them within a domain-wide drought mask, and (iii) preserve small/isolated clusters that may later coalesce with other* *clusters, thereby affecting the reconstructed event trajectories and cumulative affected-area metrics.*

Concerning the relationship to Díaz et al. (2019) and Herrera-Estrada et al. (2017), we use these studies as representative examples of object-based clustering/tracking frameworks and we clarify in the revised manuscript what is different in our implementation: we retain and track all coexisting drought objects within a given time step, allowing multiple events to evolve simultaneously in distinct regions without discarding secondary objects. This is important because secondary objects can later merge with larger ones (changing total affected area and event evolution), and because different regions may experience drought dynamics driven by different precipitation-generating mechanisms.

Finally, we revised the captions of Figures 3 and 5 to explicitly define the background colors: white indicates cells/time steps that do not meet the drought criterion (non-drought), and grey indicates the domain/background (or non-analysed/no-data areas, depending on your convention), while the colored patches correspond to drought clusters/events. (We made this explicit to avoid ambiguity.)

Comment:

"Could the authors explain why affected area has a more stable and consistent evolution? Is it due to higher diagonal values?"

Response:

Thank you for this question. Yes, the higher diagonal values are a direct quantitative indication of higher stability: in a transition matrix, diagonal entries represent the conditional probability of remaining in the same phase from $t$to $t+1$. Therefore, when the affected-area matrix shows larger diagonal probabilities than the severity matrix, it means that the affected-area phase (Expansion/Persistence/Contraction) is more likely to persist between consecutive months, i.e., a more stable and consistent evolution.

We also clarify the physical interpretation behind this pattern. Affected area is a spatial-integrated indicator of how far drought conditions extend at a given time. At a monthly time step, spatial footprints often evolve with inertia: once a contiguous drought footprint is established, its boundaries tend to shift gradually rather than oscillate rapidly, because neighbouring grid cells typically transition in/out of drought in a spatially coherent way. In contrast, severity (e.g., deficit intensity/accumulated anomaly within the footprint) can respond more quickly to short-term rainfall variability within already drought-affected regions, producing more frequent phase switching and thus lower di*agonal probabilities.*

Added text:

"In contrast, affected area displays higher phase retention. If the drought is in Contraction at time t, it is more likely to remain in Contraction at $t + 1$ (P = 0.60) than to shift to Persistence or Expansion (P = 0.37 and 0.03, respectively). The same tendency of higher diagonal probabilities (phase persistence) is also observed for the Persistence and Expansion rows. This quantitatively explains why affected area exhibits a more stable and consistent evolution: larger diagonal entries imply that the footprint is more likely to remain in the same phase from one month to the next. From a physical perspective, this reflects the spatial inertia of drought footprints: once drought conditions become spatially connected, the boundary of the affected area tends to expand or contract gradually in a spatially coherent manner, whereas severity (intensity within the footprint) can respond more rapidly to short-term rainfall variability, producing more frequent phase switches at monthly resolution."

Additional editorial improvements

We also corrected minor wording and formatting points raised in your line-by-line notes (e.g., phrasing such as "proposed by Andreadis et al.", removal of redundancies, and minor caption and grammar edits) to ensure consistency and readability.

We hope these revisions address your concerns fully and make the manuscript clearer and more accurately positioned. Thank you again for your time and constructive guidance.

Sincerely,

João Dehon Pontes Filho
(on behalf of all co-authors)