The dynamics of spatio-temporal droughts in Northeast Brazil

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Abstract.

Droughts are complex spatiotemporal phenomena that challenge effective monitoring and response. This study introduces a novel analytical framework that simplifies drought characterization. Building on three-dimensional (3D) drought analysis, we introduce three new evolution metrics—Growth Curve, State Curve, and Dynamic Curve. This framework allows clear assessment of drought evolution through its expansion, persistence, and contraction phases. Applied to Northeast Brazil, a semi-arid region with recurrent severe droughts, the method identified four main typologies of drought progression. Most droughts in the region exhibit a characteristic pattern of rapid expansion, long persistence, and abrupt contraction, reflecting a typical signature of regional climate variability. Recognizing such recurrent evolution patterns provides decision-makers with an evidence-based understanding of how droughts tend to evolve, supporting more timely and region-specific management actions. The proposed framework thus bridges the gap between scientific drought analysis and practical preparedness planning, breaking the complexity dilemma of scientific information that is hard to apply in operational applications. Its flexible structure can be adapted to other drought indices and regions, offering a transferable tool to strengthen proactive drought governance worldwide.

Highlights

1. Proposes Growth Curve, State Curve, and Dynamic Curve to systematically track drought expansion, persistence, and contraction.
2. Identifies four distinct drought evolution typologies, improving predictability and proactive planning.
3. Reveals that Type II droughts (rapid expansion, long persistence, abrupt contraction) are the most prevalent in Northeast Brazil, giving insights in how to plan for proactive drought management.

Keywords:

Drought Analysis; Drought Evolution; Drought Typology

1 Introduction

Droughts can exhibit significant spatial heterogeneity, with their severity and affected area changing over time (Andreadis et al., 2005a; Vicente-Serrano, 2006a). Despite their spatio-temporal nature, early studies on drought characterization focused primarily on the temporal dimension, often using run theory to analyze drought events independently from the original time series (Yevjevich V, 1967, Espinosa et al., 2019; Liu et al., 2019; Shiau, 2006). To incorporate spatial variability, researchers began using regionalization techniques such as Thiessen polygons and statistical clustering methods like Principal Component Analysis (PCA) and K-means (Portela et al., 2015; Vicente-Serrano, 2006b; Zhou et al., 2019). However, these approaches assume fixed spatial boundaries, which do not align with the fluid nature of drought propagation.

Recent advancements in drought research have introduced methodologies capable of tracking drought movement in both space and time. Building on the concept of severity-area-duration (SAD) curves, proposed by Andreadis et al. (Andreadis et al., 2005a), subsequent studies have developed 3D clustering algorithms (longitude, latitude, and time) to analyze drought trajectories (Diaz et al., 2018, 2019; Herrera-Estrada et al., 2017; Herrera-Estrada and Diffenbaugh, 2020; Lloyd-hughes, 2012). However, a key limitation of many advanced 3D clustering methods, including those by Herrera-Estrada et al. (2017) and Diaz et al. (2019, 2020), is that while they provide robust tracking of drought dynamics and detailed statistical characterization of attributes like displacement, growth, and intensification rates, they often result in complex analytical outputs. These outputs, though scientifically rigorous, frequently emphasize descriptive statistics or intricate visual depictions that can be challenging for non-specialists to synthesize into structured, actionable insights for decision-making. For instance, Herrera-Estrada et al. (2017) meticulously analyze how drought clusters displace and change in area and intensity, but the focus remains on the statistical patterns of these dynamics rather than providing a simplified, diagnostic framework for event evolution.

Despite significant advances in drought analysis and monitoring, a fundamental challenge persists: adopting models that are either overly simplistic, failing to capture key spatiotemporal characteristics, or excessively complex, limiting their practical application for decision-makers. This "complexity dilemma" highlights the necessity for methodologies that strike a balance between analytical robustness and practical applicability in order to improve drought mitigation and adaptation strategies.

To overcome these limitations, researchers have increasingly adopted event-based frameworks that present spatio-temporal drought characteristics. For instance, Andreadis et al. (2005) introduced severity–area–duration (SAD) curves, which combine spatial extent and severity over different durations to construct envelopes of extreme drought events. More recently, Chen et al. (2023) and Banfi et al. (2024) proposed the use of Normalized Area–Time Accumulation (NATA) curves, which allow retrospective evaluation of the temporal accumulation of drought-affected areas and provide insight into the phases of growth and recovery, an analytical step subsequent to event detection. This highlights the ongoing need for methodologies that can bridge the gap between complex scientific analysis and intuitive, decision-support tools. These methodologies represent significant advances in describing the magnitude and structure of historical spatio-temporal droughts, and they have also inspired typology-based classifications that cluster events with similar trajectories.

Despite these contributions, existing methods face important limitations. SAD curves are powerful for quantifying magnitude and comparing extremes, but they do not explicitly capture *how* a drought evolves within its lifespan. NATA curves summarize cumulative trajectories, but they represent each event with a single curve, making it difficult to identify turning points between distinct phases of a drought. Moreover, while recent studies have proposed typologies from NATA-based analyses (Chen et al., 2023; Banfi et al., 2024), these are primarily descriptive and do not provide explicit probabilistic measures of drought phase transitions.

In response to this persistent "complexity dilemma," this study proposes a novel framework that rebalances analytical robustness with practical applicability in 3D drought assessment. The explicit aim is to provide more structured and interpretable information to enhance drought evolution characterization, giving insights into to proactive preparedness planning. In this study, we propose a three-curve analytical framework that advances the characterization of spatio-temporal drought dynamics by introducing three complementary measures: the State Curve (evolution of a drought characteristic such as affected area or severity), the Growth Curve (its cumulative integral), and the Dynamic Curve (its first derivative). This framework enables droughts to be easily decomposed into expansion, persistence, and contraction phases, which are then used to define four distinct typologies of drought evolution. Importantly, we further incorporate a transition matrix that quantifies the likelihood of moving between phases, providing a probabilistic representation of drought dynamics.

This structured framework then enables the proposition of actionable typologies of drought evolution, which serve as a simplified yet comprehensive classification system for decision-makers. These typologies translate complex spatio-temporal dynamics into predictable behavioral patterns, offering more direct guidance for proactive planning by identifying how individual droughts are likely to evolve and persist. For instance, knowing that a region is predominantly affected by 'Type II' droughts (rapid expansion, long persistence, abrupt contraction) can inform the design of early warning systems and resource allocation strategies, emphasizing quick response to onset and sustained support during the persistence phase. This level of practical applicability is a significant added value compared to existing 3D clustering methods that primarily focus on describing trajectories or broad event categories based on aggregated properties

By simplifying complex spatio-temporal drought analyses into an accessible typology, this study contributes to bridging the gap between advanced analytical methods and the practical needs of decision-making in drought-prone regions. It complements and extends existing methodologies by introducing probabilistic information on changing drought evolution, thereby offering new tools for comparative research and for the long-term planning of drought risk management.

2 Materials and methods

The methodology to classify the evolution of drought events in the proposed typology follows the following steps: 1) Definition of spatio-temporal droughts events; 2) Definition of spatio-temporal drought characteristics; 3) Analysis of drought event evolution using Three-curve model; 4) Classification of drought evolution according to proposed typologies; and 5) Probabilistic analysis of changing phase using transition matrix. Figure 1 shows the schematic workflow of the full procedure.

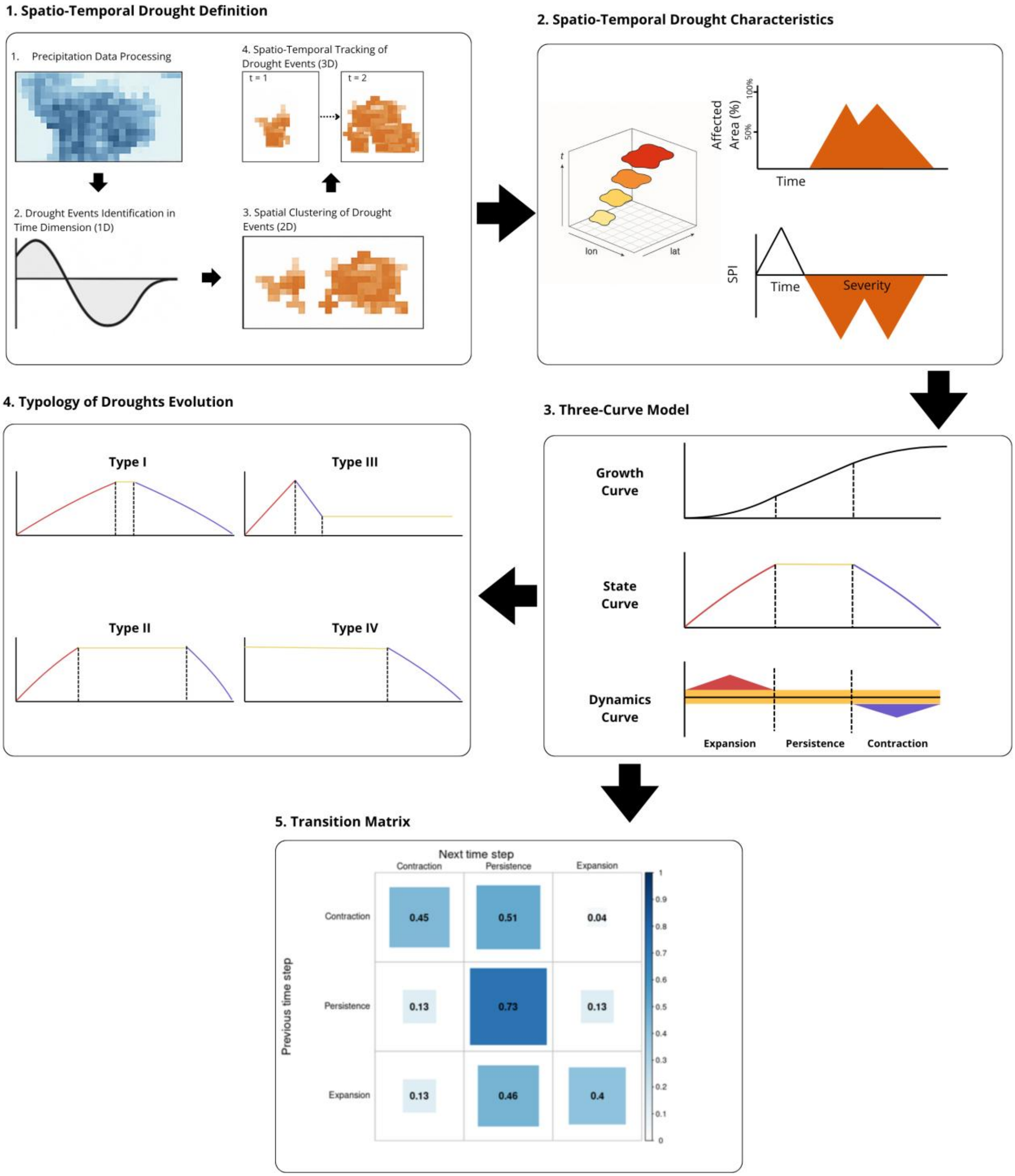

Figure 1: Schematic workflow proposed to classify the evolution of drought events. The first panel shows the definition of spatial-temporal drought events. The second shows the Three-curve model and the third panel show the proposed drought evolution typologies.

2.1 Spatio-Temporal Drought Definition

The spatio-temporal drought definition is divided into four steps: (i) Precipitation data processing; (2) Drought event identification in the time dimension (1D), (3) Spatial clustering of drought events (2D), and (4) Spatio-temporal tracking of drought events (3D).

Step 1: Precipitation Data Processing

The first step for drought spatio-temporal definition is data processing. It requires gridded data to support the spatial analysis. Monthly precipitation data were sourced from the CRU TS v4.05 dataset, which has a spatial resolution of 0.5° × 0.5° and covers the period from 1950 to 2018 (Harris et al., 2020). Although the CRU TS v4.05 time series extends back to 1901, we opted to use data from 1950 onward due to the limited availability of rain gauge records in the study region during the early 20th century, which could introduce uncertainties in data interpolation.

The Standardized Precipitation Index (SPI) was calculated for each grid cell using a Gamma probability distribution fitted to the precipitation time series (Mckee et al., 1993). While SPI is widely recognized for its simplicity and comparability, its exclusive reliance on precipitation can be perceived as a limitation for fully capturing the complexities of multifaceted droughts, especially in light of modern advancements in drought assessment (Mishra and Singh, 2010). However, it is crucial to emphasize that the primary objective of this study is to introduce and validate a novel methodological framework for spatiotemporal drought evolution analysis, rather than to advocate for a single, specific drought indicator.

For the Northeast Brazil (NEB) case study, SPI was deliberately chosen due to compelling regional data availability advantages. In NEB, precipitation data boast significantly longer historical series and a much denser monitoring network compared to other hydro-meteorological variables. For instance, the meteorological network in NEB that measures evaporation represents approximately only 10% of the pluviometric network. This stark difference in data density and historical depth makes precipitation-based indices, particularly SPI, the most robust and reliable choice for demonstrating the capabilities of our spatiotemporal tracking methodology in this specific region. Therefore, while we acknowledge the increasing importance of multi-indicator approaches for comprehensive drought characterization, especially for agricultural or hydrological impacts, the use of SPI in this context allowed us to leverage the highest quality and most extensive historical data available for NEB to rigorously test our novel framework.

Also, since precipitation is the most widely available climatic variable, the World Meteorological Organization recommends using the Standardized Precipitation Index (SPI) for drought analysis. The SPI offers three key advantages: (i) it relies solely on precipitation, making it simple to calculate; (ii) it provides standardized values, allowing for easy regional comparisons; and (iii) it accommodates different timescales, making it applicable to agricultural, hydrological, and socioeconomic drought assessments (Hayes et al., 2007; Pontes Filho et al., 2019).

Despite the choice for using SPI, the proposed methodology is designed to be versatile and can be applied to any gridded time-series of a drought index. Future studies could incorporate additional indices such as SPEI (Standardized Precipitation Evapotranspiration Index) or PDSI (Palmer Drought Severity Index) to improve drought characterization as the methodology proposed in this study for the drought spatio-temporal analysis fits any grided time-series of drought index and any drought definition.

Step 2: Identification of Drought Events in the Time Dimension (1D)

Run theory (Yevjevich V, 1967) was applied to detect continuous periods in which SPI values remained ≤ -1.0 in each grid cell. Drought perception varies among users, as water shortages impact different sectors at different times. Shorter time scales, such as 1 to 3 months, can be more critical to agricultural users who do not irrigate their cultures. Longer time scales, such as 6 to 12 months, may relate to hydrological impacts on urban and irrigation water supplies. Thus, the aggregation period and the threshold selected can strongly impact drought analysis. We used SPI 12 for our analysis as the region presents strong seasonality and it is highly dependent on pluriannual water reservoirs. But another time-scale could also be used.

Step 3: Spatial Clustering of Drought Events (2D)

Each grid cell experiencing drought was analyzed spatially to identify clusters of connected drought areas. An 8-neighbor connectivity rule was applied, defining a drought cluster as a set of adjacent grid cells where SPI ≤ -1.0 simultaneously in the same time-frame. To avoid identifying small, localized events, a minimum affected area threshold of 1.6% of the total study area was used (Xu et al., 2015).

More than one cluster of affected areas can occur at the same time-frame. At this step, they will only be considered as a single event if they are contiguous. However, this condition can change as we will see in step 4.

Step 4: Spatio-Temporal Tracking of Drought Events (3D)

The generation of these three-dimensional drought events, which inherently accounts for their spatial extent and temporal continuity, is achieved through a multi-step clustering and tracking algorithm. Drought clusters were tracked over time to analyze their evolution and propagation paths. A drought event was considered continuous if at least 1.6% of its area overlapped between consecutive months. This specific overlap threshold of 1.6% was adopted in this study, consistent with established criteria used in previous spatiotemporal drought analyses by Li et al. (2020) and Xu et al. (2015). This choice reflects a common practice in the literature and this filter is important for distinguishing significant spatio-temporal connections while filtering out minor, ephemeral overlaps that may not represent a continuous drought event.

Through this methodology, each drought event evolving in space and time is assigned to a unique ID. If, at some point, two distinct clusters coalesce at a future point in time, all cells that were previously identified as belonging to separate clusters will now be considered part of a single cluster. This transformation occurs even if these cells were not in direct contact with one another in the past. Consequently, it is possible for a single event to encompass regions that are not contiguous, provided that these regions have been in contact with one another at some point during the event's duration. The present approach entails the reclassification of all the clusters as belonging to the same larger event, on the basis that the driving climatic variables are the same (Andreadis et al., 2005a). This procedure permits drought events to exhibit variability in both duration and spatial extent, and are not confined to a predefined climate region.

An important consideration in the proposed algorithm is that when a cluster splits into two or more clusters, they all retain the same initial ID. This is a modification of the algorithm used by Diaz et al. (2019) and Herrera-Estrada et al. (2017), whose analysis only preserved the areas of the largest clusters. We chose this path because droughts can occur simultaneously in different regions due to different precipitation mechanisms affecting each region. Therefore, conserving only the largest area may artificially interrupt an event that is still occurring or even completely ignore an event that occurred simultaneously but in different regions.

2.2. Spatio-Temporal Drought Characteristics

Drought characteristics represent the various dimensions through which drought events manifest and evolve across time and space — including their duration, severity and affected area. Each characteristic provides a complementary perspective: severity indicates the magnitude of the water deficit; the affected area reflects the spatial extent of the phenomenon; duration captures its persistence. Understanding these characteristics individually enables researchers and practitioners to identify not only when and where a drought occurs, but also how it develops and what impacts it may generate across different sectors. Such a multidimensional perspective enhances the responsiveness of decision-makers, allowing them to anticipate critical phases, prioritize vulnerable regions, and design targeted mitigation and adaptation strategies that improve drought preparedness and resilience.

To analyze how a single drought characteristic evolves during events' duration, an intra-event analysis is performed. In this study, we choose to analyze two drought characteristics: affected area and severity.

In this study, only affected area and severity were selected as the primary characteristics for assessing drought dynamics, as the objective is to perform an intra-event analysis that focuses on the evolution of drought behavior throughout its duration. The affected area represents the spatial extent of the cluster relative to the total studied area, indicating the overall reach of the drought event in a given moment. Severity is defined as the average of SPI values across the grid cells clustered as one drought event in a given moment. Unlike duration, which represents the temporal extent of an event and is inherently captured by the tracking of its onset and termination, affected area and severity provide complementary and dynamic insights into how droughts expand, persist, and contract over time. The affected area reflects the spatial dimension of drought propagation, while severity quantifies the intensity of the deficit within the affected region.

2.3. The Three-Curve Model

Each drought characteristic, in this study the affected area and severity, was used to compute the three-curve model:

1. Growth Curve: Cumulative of drought characteristics (Integral of State Curve).
2. State Curve: Drought characteristics.
3. Dynamic Curve: Change in state curve (1st derivative of State Curve).

The three-curve model represents an adaptation of an analytical framework originally proposed by Utsunomiya et al (2020) for monitoring the spread of COVID-19. In their study, the authors introduced three metrics: growth curve, growth rate, and acceleration, which in the present study correspond to the growth curve, state curve, and dynamic curve, respectively. This terminological modification was necessary because, in the context of COVID-19, the primary monitored variable was the growth curve. Conversely, in this study, the monitored variable is the state curve, making it inappropriate to refer to it as a rate and, consequently, to define its first derivative as acceleration.

To better characterize the spatiotemporal evolution of drought events, we introduce the Drought Phase Classifier, a methodology based on the Dynamic Curve, which represents the first derivative of the State Curve. This classifier provides insights into the dynamic phase of a drought event by categorizing it into one of three possible phases: contraction (D^-), persistence (D^0), or expansion (D^+). Understanding these phases enables a more precise evaluation of drought behavior and facilitates understanding whether a drought characteristic is intensifying, maintaining its characteristic or dissipating. Each characteristic, such as affected area or severity, exhibits independent behaviour, meaning that within a single drought event, one characteristic may be expanding while another is contracting.

In order to define the transition between phases, the dynamic curve values of each event were normalized, and thresholds of 0.75 and -0.75 were used. The rationale for the selection of this procedure was to emphasise the moments at which the drought characteristic evolves most rapidly within the event, to ascertain whether the characteristic is expanding, persisting or contracting. Consequently, the rate of evolution between these events was not deemed to be a priority at this juncture.

2.4. Typology of Droughts Evolution

To better understand the different ways in which droughts evolve over time, a typology of drought events was developed based on their State Curves evolution patterns. Four theoretical models of drought evolution were defined, each representing a distinct way in which the affected area and severity evolve throughout the event. These typologies provide insight into how droughts expand, persist, and contract, helping to better understand drought evolution in a specific region and proactively plan accordingly.

Type I: Prolonged Expansion, Rapid Persistence, and Prolonged Contraction

The Type I model represents a simplified conceptualization of droughts as slow-onset, creeping phenomenon. In this case, droughts expand gradually, experience a short persistence phase, and then enter a long contraction phase before completely dissipating. This model aligns with the idea that droughts are progressive and cumulative phenomena, following a pattern that often influences societal responses according to the hydro-illogical cycle (Wilhite, 2012). As the event unfolds, it triggers gradual awareness, progressing from alert to concern and ultimately panic as impacts intensify. However, real-world droughts often deviate from this idealized behavior, necessitating additional typologies to describe more complex evolution patterns.

Type II: Rapid Expansion, Prolonged Persistence, and Rapid Contraction

The Type II model describes droughts that expand quickly, leading to a long period of persistence, followed by a rapid contraction phase. This behavior contrasts with the gradual expansion seen in Type I and reflects situations where drought conditions develop abruptly, often due to sudden precipitation deficits or extreme climatic anomalies. The extended persistence phase suggests that the drought remains severe for an extended period, making it particularly impactful on water resources, agriculture, and ecosystems. The rapid contraction phase indicates that when recovery begins, it happens relatively quickly, likely due to intense rainfall events or large-scale climatic shifts.

Type III: Rapid Expansion and Contraction with Prolonged Persistence

In the Type III model, droughts undergo a short-lived expansion phase, followed by a similarly short contraction phase. However, rather than dissipating entirely, the drought enters a prolonged persistence phase, maintaining its intensity over an extended period. This type of drought suggests a lag in the expected precipitation, resulting in a rapid expansion, but when the rainfall finally comes, it results in a also rapid contraction, partially alleviating but not sufficiently to terminate the event. The long persistence phase that follows implies that the affected region remains under drought stress. This pattern is particularly relevant in regions where intermittent rainfall events are insufficient to break prolonged dry conditions, leading to extended periods of water scarcity and socioeconomic stress.

Type IV: Instantaneous Maximum Expansion and Rapid Contraction

The Type IV model represents droughts that begin with their maximum State Curve, followed by a long persistence phase, and end with a rapid contraction. This type can be considered a special case of Type II, but without a distinct expansion phase. The fact that these droughts immediately start at full intensity suggests that they may be triggered by sudden climatic shifts, such as the abrupt onset of long-term precipitation deficits. Their extended persistence phase means that they pose significant long-term challenges for water resource management, while their rapid contraction indicates that recovery, when it comes, is swift and driven by a major meteorological shift.

2.5 Transition Matrix for Drought Phase

To evaluate the continuity of drought phases over time and their likelihood of transitioning between phases, we employed a Transition Matrix approach. This method provides a probabilistic framework to quantify the evolution of drought dynamics by analyzing the frequency with which an event remains in the same phase or shifts to another phase in the subsequent time step.

The Transition Matrix T represents the probability of a drought event moving from one phase at time t to another phase at time $t+1$.

The transition probabilities are calculated based on the historical dataset, where the relative frequency of transitions between phases is used to estimate the likelihood of each possible phase change. The transition matrix is defined as:

$$T = \begin{matrix} P(D^+ \rightarrow D^+) & P(D^+ \rightarrow D^0) & P(D^+ \rightarrow D^-) \\ P(D^0 \rightarrow D^+) & P(D^0 \rightarrow D^0) & P(D^0 \rightarrow D^-) \\ P(D^- \rightarrow D^+) & P(D^- \rightarrow D^0) & P(D^- \rightarrow D^-) \end{matrix}$$

where $P(A \rightarrow B)$ represents the probability of transitioning from phase A at time t to phase B at time $t + 1$.

The transition probabilities were computed empirically by analysing all drought events in the historical record and counting the occurrences of each transition type. The probabilities were determined using the following equation:

$$P(A \rightarrow B) = \frac{N(A \rightarrow B)}{N(A)}$$

where:

$N(A \rightarrow B)$ is the number of times a drought event transitioned from phase A to phase B.

$N(A)$ is the total number of occurrences of phase A in the dataset.

2.6 Study Area and Data

The northern portion of Northeast Brazil (NEB), was chosen as a case study to demonstrate the proposed framework as it is a semi-arid region that frequently experiences recurrent droughts due to its high climatic variability. This region, located between 2° and 10°S and 34° and 44°W, is primarily influenced by the Intertropical Convergence Zone (ITCZ), which is the main driver of precipitation in majority of the study area (Hastenrath, 2012; Moura and Shukla, 1981; Uvo et al., 1998).

Despite the ITCZ influence, other distinct climatic mechanisms also influence different subregions of NEB. Figure 2 illustrates the seasonality of precipitation in NEB, highlighting the distinct sazonalities associated to different climate drivers. In the northern part, there is a pronounced rainy season in the from February to May, associated with the southward migration of the ITCZ. Additionally, a pre-seasonal rainfall period occurs in December and January, while dry conditions dominate the remaining months. The eastern coastline, although also impacted by the ITCZ, receives its primary rainfall input from the Southeast Trade Winds between May and July. Meanwhile, the southernmost areas, particularly in the southwest, experience rainfall due to Cold Fronts from November to January, with additional contributions from the ITCZ between February and April (Hastenrath and Heller, 1977; Uvo et al., 1998). These atmospheric systems modulate drought occurrence and evolution across the region, making it essential to understand their roles in shaping precipitation patterns.

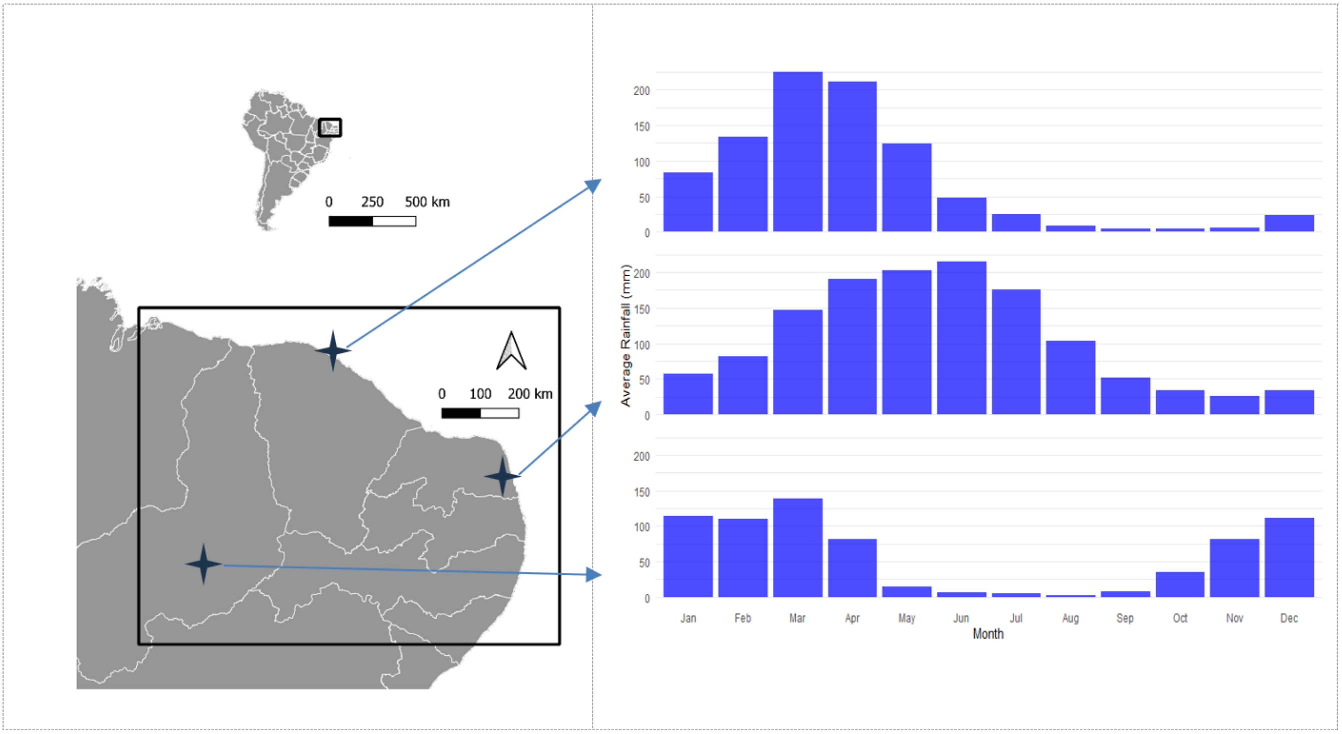

Figure 2: Location map showing the northern portion of Northeast Brazil (NEB). The rainfall charts are representative of the northern zone influenced by ITCZ, the eastern zone influenced by Southeast Trade Winds, and the southern zone influenced by Cold Fronts. Rainfall data CRU TS v4.05 from 1950 to 2018.

3 Results

3.1 Drought Spatio-Temporal Definition

Understanding how droughts evolve within an event is critical for improving real-time monitoring and early warning systems. Unlike traditional drought assessments that provide static snapshots of specific areas under drought, this intra-event analysis tracks the temporal and spatial evolution of drought severity and affected area. By identifying key moments of expansion, contraction, or persistence of severity and affected area in drought progression, this approach provides actionable insights for water resource management.

The 3D spatio-temporal drought definition algorithm enables the delineation of the cluster of contiguous cells that are affected by the same drought event, even in the case of simultaneous drought events, i.e., those that occur in the same time interval but never coalesce.

One of the key advantages of the proposed algorithm over the one used by used by Diaz et al. (Diaz et al., 2019) and Herrera-Estrada et al. (Herrera-Estrada et al., 2017), is its ability to identify and analyze multiple drought events occurring simultaneously in time but in distinct spatial regions. This capability is illustrated in Figure 3, which depicts three separate drought events within the study area: Event A, which lasted from May 1987 to January 1988 and was located in the northwestern portion of the study area; Event B, which occurred between August 1987 and June 1988, affecting the southwestern region; and Event C, which lasted from October 1987 to March 1988 and was concentrated in the central-northern sector of the study area.

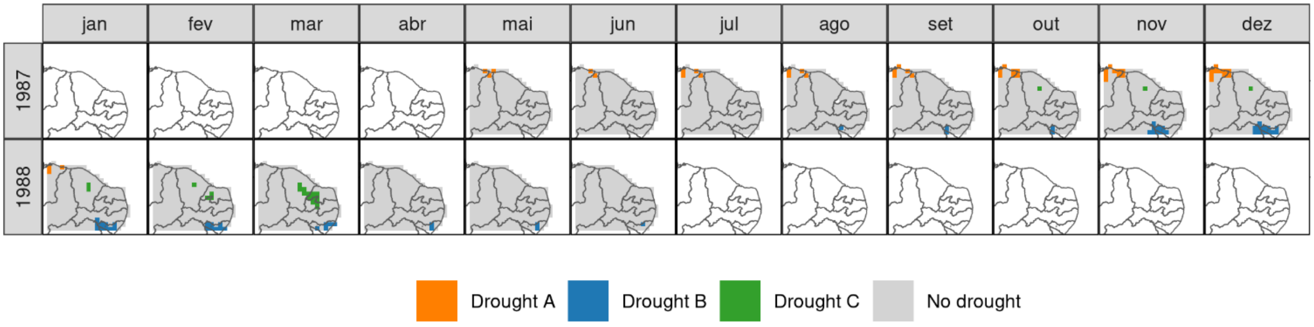

Figure 3: Map of the spatio-temporal drought evolutions of three drought events that occurred simultaneously during the years of 1987-1988.

By distinguishing and evaluating individual drought events that impacted different regions at the same time, the algorithm provides a more specific understanding of drought dynamics, acknowledging that different parts of the study area are influenced by distinct precipitation-generating mechanisms. This is particularly relevant in Northeast Brazil, where the Intertropical Convergence Zone (ITCZ), Southeast

Trade Winds, and cold fronts drive precipitation patterns in different sub-regions (Costa et al., 2018; Hastenrath, 2012; Nobre and Shukla, 1996; Uvo et al., 1998).

The ability to isolate co-occurring drought events is especially valuable for large-scale analysis, such as continental and global drought assessments, where simultaneous droughts in different regions could be driven by varied climatic drivers and teleconnections. This methodological enhancement allows for more precise drought characterization, ultimately contributing to improved monitoring, forecasting, and mitigation strategies.

3.2. Drought Spatio-Temporal Characteristics

The 3D cluster-based analysis of drought events allows for a comprehensive evaluation of their spatial and intensity characteristics. In this study, we assess two independent variables: (i) affected area, defined as the percentage of the total study area that is contiguously under drought conditions at a given time, and (ii) severity, measured as the mean SPI value of all grid cells within the drought cluster at that moment. These two characteristics provide complementary perspectives on drought evolution, as they do not necessarily follow the same trajectory over time.

The independent behavior of affected area and severity has important implications for drought monitoring and decision-making. While, in some cases, these variables exhibit strong agreement, with severity increasing as the affected area expands, in other cases, they follow divergent patterns, indicating that spatial extent and drought intensity may evolve differently throughout an event. Figure 4 highlights this contrast by presenting the evolution of these two characteristics in two distinct drought events. In the first case, the 1968-1969 event, both affected area and severity increased simultaneously, suggesting that the drought not only expanded but also intensified over time. In the second case, the 1987-1988 event, however, affected area and severity evolved in opposite directions, with one increasing while the other remained stable or even decreased.

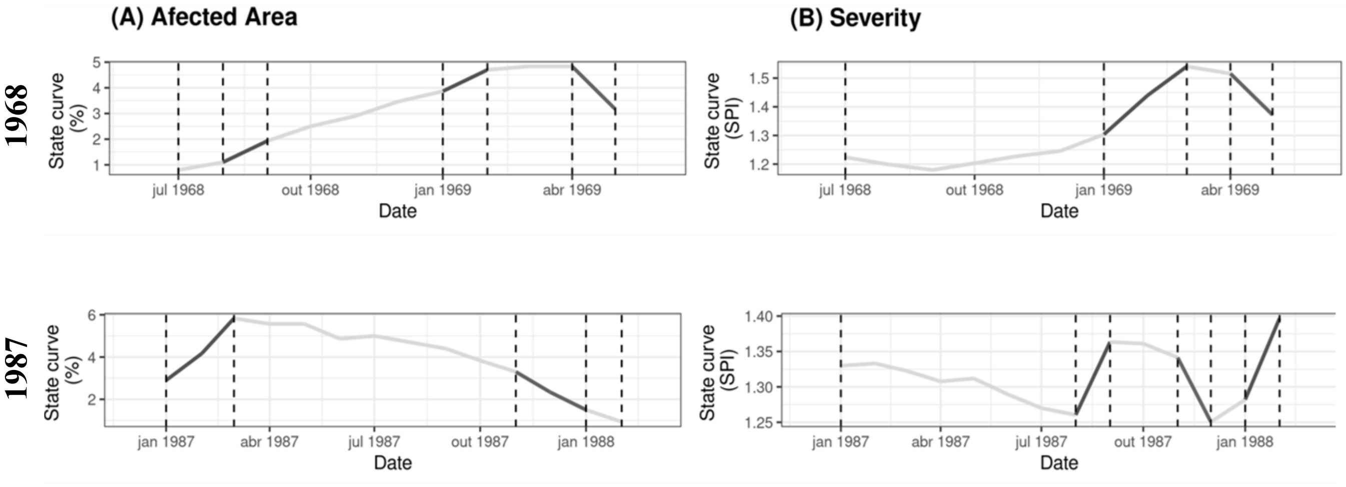

Figure 4: The evolution of the two drought characteristics analyzed, affected area, and severity, for the 1987 drought event over time.

This discrepancy underscores the importance of considering both variables simultaneously in drought assessments. A drought that affects a large area but maintains moderate severity may affect the alternative water sources that could be shared to mitigate impacts, whereas a highly severe drought within a more localized area may pose acute agricultural productivity. Thus, relying solely on one of these indicators could lead to an incomplete understanding of drought impacts, reinforcing the need for a multidimensional approach in monitoring, forecasting, and management strategies.

3.3. Application of the Three-Curve Model

To enhance the understanding of drought evolution and facilitate decision-making, a drought phase classifier was developed. This classifier enables the identification of different phases of a drought event, categorizing moments in which a drought characteristics—affected area or severity—are expanding, persisting, or contracting.

The classification is based on the dynamics curve, the last component of the three-curve model, which represents the first derivative of the state curve. The state curve itself is defined as the state variable of the drought characteristics itself. Additionally, the growth curve offers an integrated view of the accumulated impact of the drought, making it easier to visualize the evolution of the affected area (percentage-wise) and the cumulative severity over time.

By defining these phases and structuring the three-curve model—growth curve, state curve, and dynamics curve—decision-makers can easily interpret how historical drought events evolved. This structured approach not only provides insights into drought evolution but also supports proactive decision-making, allowing authorities to plan mitigation measures specifically tailored to how droughts evolve in their regions.

Figure 5 and 6 illustrate an example of the visualization of a drought event using the three-curve model. The growth curve reflects the cumulative impact, the state curve provides the current drought status, and the dynamics curve captures transitions between expansion, persistence, and contraction phases. It also presents the spatio-temporal evolution map to facilitate understanding of how the affected area evolved during the event.

By comparing the spatio-temporal evolution of the drought in the map and with the 3 curves model, it is easy to understand that the event initially started small but expanded rapidly in December 1990, covering a large portion of the study region. The month of December is characterized by the onset of the pre-rainy season, a period that typically is expected some amount of precipitation that precedes the main precipitation period. However, this year was an exception, as precipitation was absent during this time, thereby marking the commencement of the expansion phase. By March 1991, with the onset of the rainy season, the drought began to fragment, becoming restricted to fewer areas. The map shows small fragments of droughts. These are still regarded as the same event, given the fact that they will be connected in the future. In 1992, the event remained concentrated in the northwestern portion of the region, where it persisted until January 1993. The analysis indicates that both the State Curves of the affected area and the Severity demonstrate a persistent phase during this period. In the beginning of 1993, a new rainy season failed to deliver sufficient precipitation, leading to another expansion of the drought, both in terms of affected area and severity. Following this rapid expansion of the two characteristics, the state curves remained in a persistent phase for a considerable period, until in 1994 there was a rapid contraction of the two variables with the advent of the new rainy season, thereby bringing the drought event to a conclusion in May of that year.

In this case, the affected area and severity exhibited similar behaviours, suggesting a coupled relationship between spatial expansion and drought intensity. As the drought expanded spatially, its severity also increased, while during the contraction phase, both variables simultaneously decreased. This alignment indicates that the absence of the primary rain-producing mechanism during expected wet periods not only increased the total affected area but also amplified drought severity. However, this is not a generalized behaviour across all drought events, as demonstrated throughout this study. Therefore, monitoring these two variables is essential for an accurate understanding of drought progression and its potential impacts.

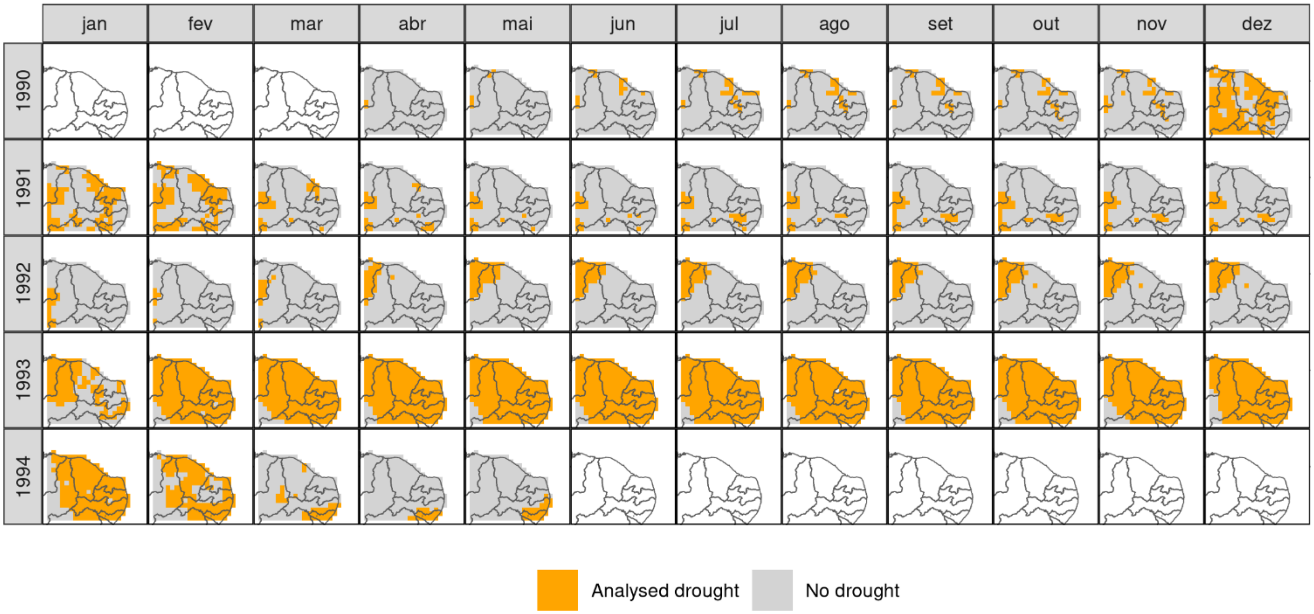

Figure 5: Spatio-Temporal Drought Map of the 1990-1994 drought event over time

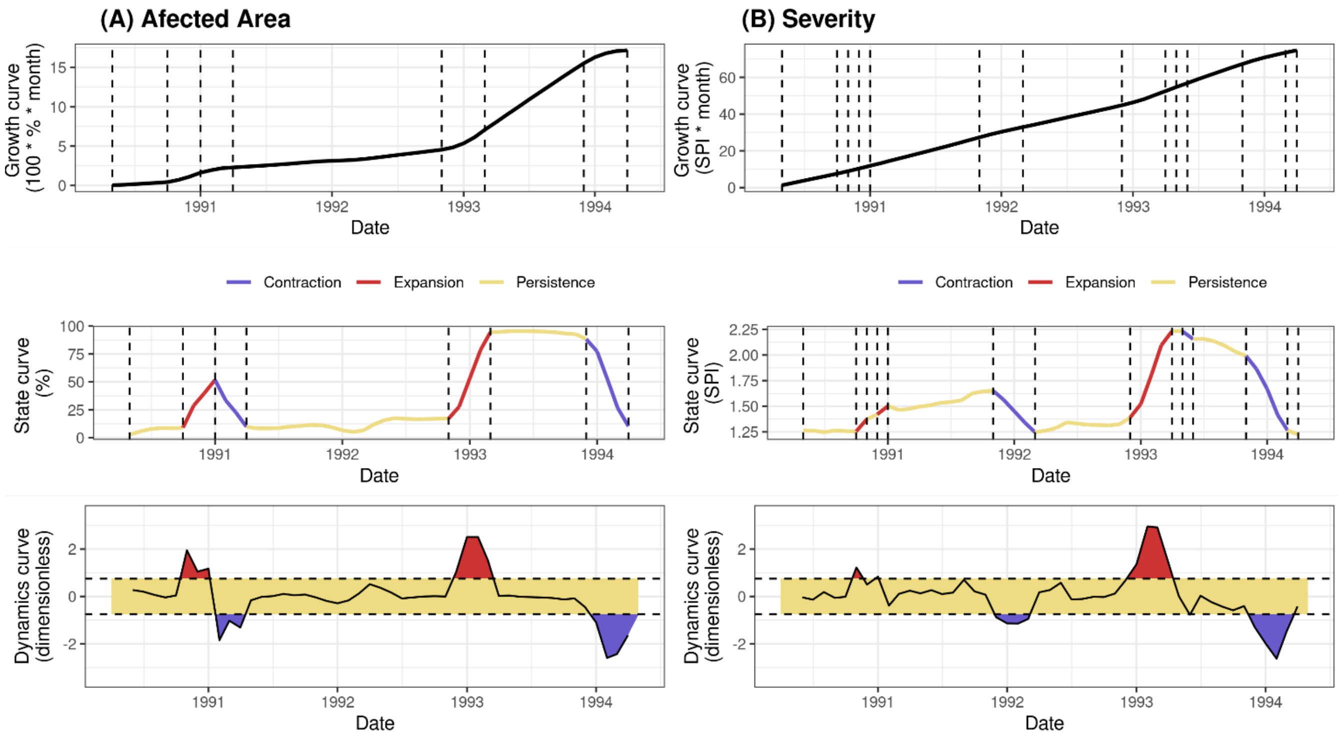

Figure 6: Spatio-Temporal Drought Map and 3 Curves Model for Affected Area and Severity, showing the evolution of the 1990-1994 drought event over time.

3.4. Typology of Droughts Based on Evolution Dynamics

Using the 3D space-time drought analysis, we identified the 22 drought events. Since many of these events spanned multiple years, different dynamical evolution patterns could be observed within a single event. As a result, a total of 25 drought evolution classifications were visually assigned across the 22 events analyzed.

Figure 8 presents the four proposed theoretical types along with an observed case of affected area evolution for each typology. Type I, characterized by a long expansion phase, rapid persistence, and prolonged contraction, was observed in an event between October 1987 and April 1988. Type II, which exhibits rapid expansion, long persistence, and short contraction, is exemplified by an event spanning from 1987 to 1988. In this case, persistence occurred with a gradual decline, though not sufficiently steep to transition into the contraction phase for an extended period. It was only at the end of 1987 that the transition to contraction occurred. Type III, defined by a rapid expansion followed by a swift contraction and subsequent prolonged persistence, was observed in the year 1966. Finally, the 1961 event exhibited a behavior similar to Type IV, which is characterized by an almost negligible expansion phase and long persistence before contraction. In the observed case, the event showed intermittent alternations between persistence and rapid expansion; however, overall, it followed the expected pattern of Type IV. It is important to highlight that the theoretical models are not strictly adhered to in the observed cases, and a visual assessment of each event is necessary to properly classify them within the proposed typology.

For the studied area, the most frequently observed drought type was Type II, representing 48% of the cases. This was followed by Type III (24%), Type I (20%), and Type IV (8%). In terms of severity, the dominance of Type II was even more pronounced, comprising 68% of classifications, while Type III, Type IV, and Type I accounted for 20%, 8%, and 4%, respectively.

These results indicate that, for the study region and under the methodological framework used for drought detection, Type II droughts—characterized by rapid expansion, long persistence, and rapid contraction—are the most prevalent form of drought evolution in the analyzed characteristics.

By knowing the predominant type of drought evolution in a specific region, decision-makers can proactively plan accordingly to the expected behavior. In the studied region, the predominance was for Type II droughts. This pattern can be attributed to the strong seasonality of precipitation in the region. Approximately 80% of annual rainfall occurs within just four months, meaning that long dry periods are a recurring feature of the climate. Additionally, the use of SPI-12 as the drought indicator, which aggregates precipitation over a 12-month period, likely enhanced the persistence of events by smoothing out short-term fluctuations and reinforcing the identification of extended drought periods.

The classification of drought evolution types provides valuable insights for policymakers, water managers, and agricultural planners, as different drought dynamics demand different response strategies.

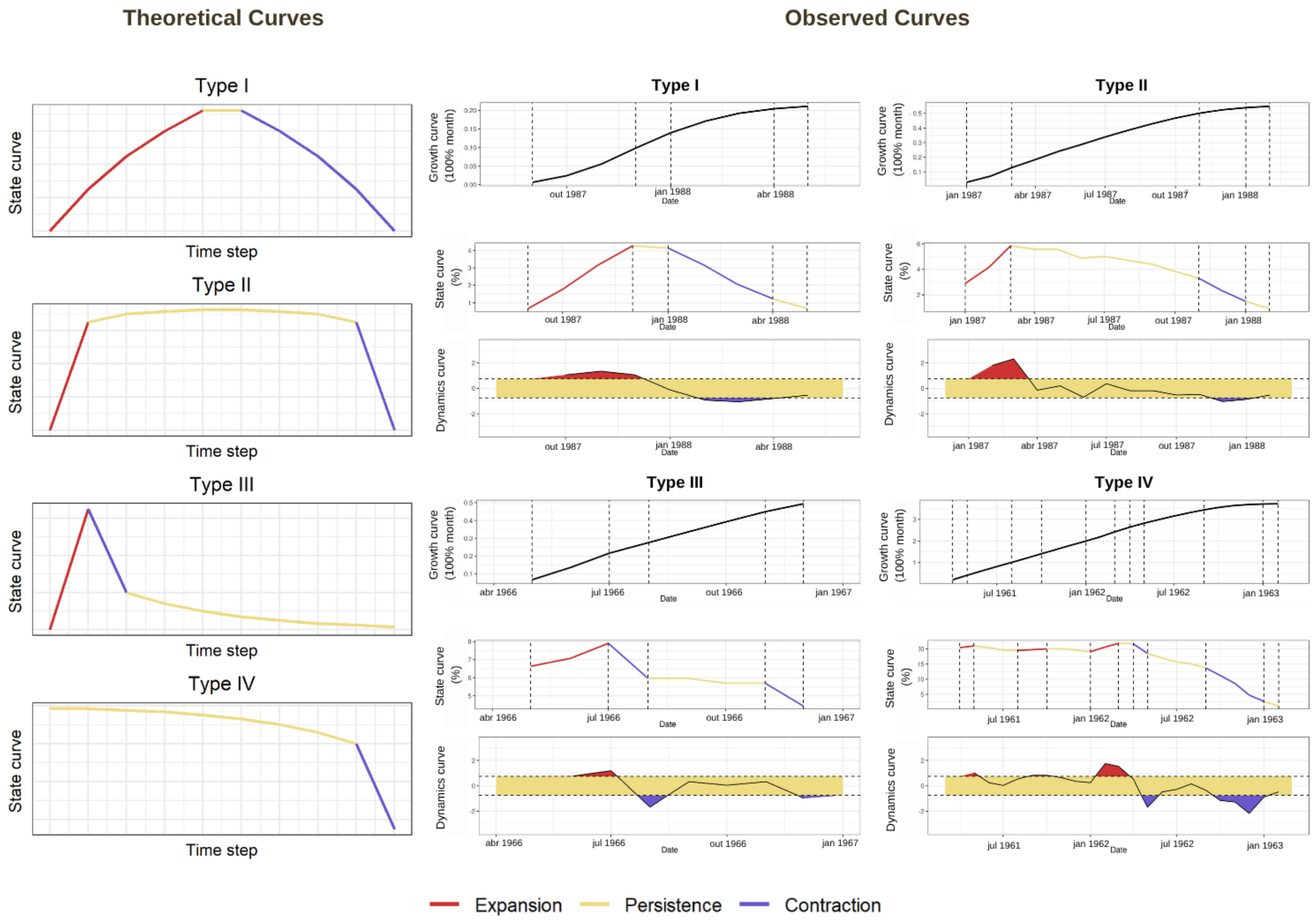

Figure 8: Theoretical and Observed Curves according to proposed typologies

The predominance of Type II droughts suggests a need for long-term preparedness and adaptive management strategies. Since these droughts expand rapidly, decision-makers must act early during the initial stages to implement mitigation measures before widespread impacts occur. The long persistence phase means that water resource planning and agricultural adaptation must be structured for prolonged dry conditions. The rapid contraction at the end of these droughts highlights the importance of monitoring systems that can quickly detect recovery periods to optimize water release policies and agricultural replanting strategies.

Type IV, as a special case of Type II, also requires strong emphasis on rapid response mechanisms. Since these droughts immediately start at full, or almost full intensity, emergency measures such as water rationing, agricultural subsidies, and drought relief programs must be deployed swiftly. Given their relatively short contraction phase, decision-makers must also ensure that recovery plans are synchronized with the return of wetter conditions, avoiding prolonged socio-economic disruptions.

Type I droughts, which involve gradual expansion, emphasize the need for sustained monitoring and proactive intervention, because adaptation measures cannot wait too long to be implemented, at the risk of being too late to mitigate impacts. Type III occurs due to a late rainy season, and can strongly impact on the agricultural sector, with a lack of rainfall in the expected period. These droughts may initially appear less severe, but their persistence means that gradual depletion of water resources and long-term agricultural stress can become major concerns.

By integrating this typology into drought preparedness plans, governments and institutions can enhance their ability to anticipate, monitor, and respond to droughts in a way that is tailored to the specific evolution pattern of each event. This approach reduces uncertainty, improves resource allocation, and strengthens the region's overall resilience to drought conditions.

Unlike operational monitoring tools such as Brazil's Drought Monitor, the proposed framework is explicitly an a posteriori method: it classifies droughts only after their full occurrence. Nevertheless, this retrospective perspective is valuable in two complementary ways. For researchers, it provides a structured and comparable language to analyze and classify droughts across regions and periods, complementing existing approaches such as SAD and NATA curves by emphasizing phase dynamics rather than aggregated envelopes. For decision-makers, it offers an interpretable typology that highlights recurrent patterns of drought behavior. While not designed for real-time early warning, the identification of dominant drought types in Northeast Brazil provides insights that can inform drought preparedness planning, guide the design of water allocation policies, and support the tailoring of mitigation strategies to regional drought behaviors.

3.5. Transition Matrix Analysis of Drought Phases

To further investigate the temporal dynamics of drought evolution, a transition matrix was developed, consolidating all drought events analyzed in this study. The diagonal elements of the transition matrix indicate the probability of a drought event remaining in the same phase, whereas the off-diagonal elements describe the probability of transitioning to another phase. Higher values along the diagonal suggest a strong persistence of each phase, whereas higher off-diagonal values indicate frequent transitions between phases.

By analyzing the transition matrix, it is possible to identify dominant drought behaviors, such as whether droughts tend to remain in a single phase for extended periods, and assess the likelihood of phase transitions, helping to determine whether a drought in a given phase is likely to intensify, stabilize, or weaken. Figure 7 presents the results of this analysis, providing insights into the stability and transition patterns of the drought characteristics.

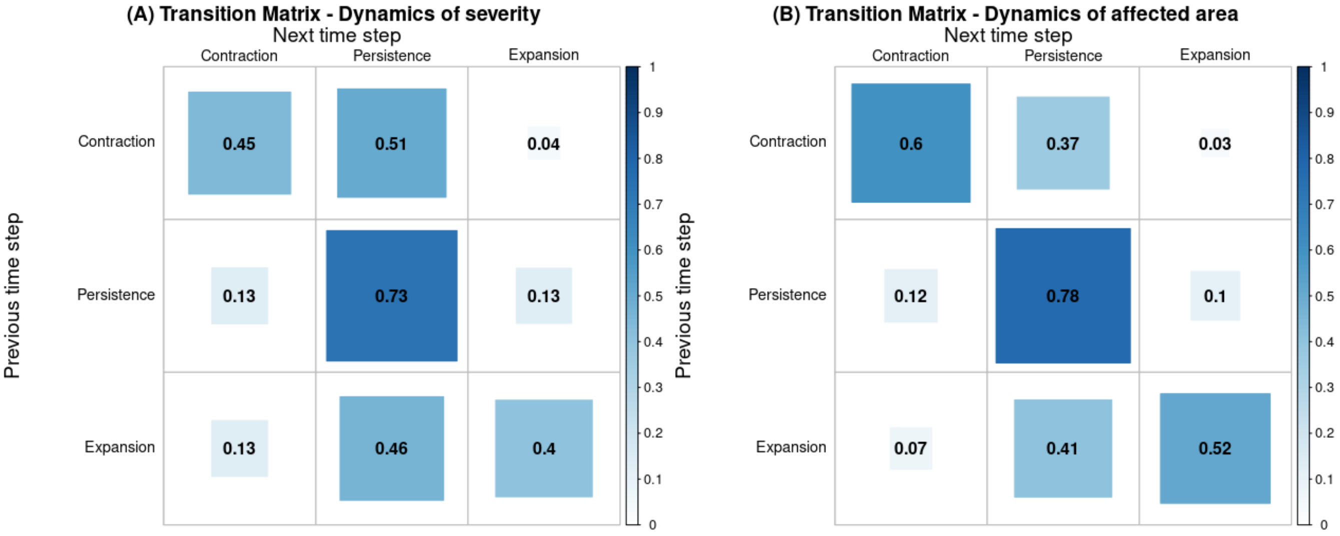

Figure 7: Transition matrix indicating the probability of a drought event remaining in the same phase or transitioning to another. Higher values along the diagonal suggest a strong persistence of each phase, whereas higher off-diagonal values indicate frequent transitions between phases.

From the transition matrix, it is evident that the main diagonal holds the highest values for the affected area, indicating that drought phases tend to persist in their current phase most of the time. This means that, once a drought is in a phase of expansion, persistence, or contraction, it is more likely to remain in that phase rather than transition. However, for severity, a different pattern emerges: the highest transition probabilities are observed at the extremities (expansion and contraction) shifting towards persistence. This suggests that, unlike the affected area, drought severity tends to stabilize more quickly, remaining in a persistent phase before transitioning again.

An important additional insight from this analysis is that severity appears to exhibit a more erratic behavior compared to the affected area, suggesting that it varies at a higher frequency than affected area. This increased variability or noise in severity could introduce challenges for its direct use in decision-making, as its fluctuations may not always indicate meaningful long-term trends. In contrast, the affected area displays a more stable and consistent evolution, making it a more reliable indicator for drought monitoring and response strategies. This finding highlights the importance of prioritizing affected area in drought assessment frameworks, while using severity as a complementary metric rather than the primary driver for decision-making.

These findings reinforce the importance of understanding the temporal behavior of each drought characteristic separately, as area and severity exhibit distinct transition tendencies. The predominance of persistence for severity implies that once drought intensity reaches a certain level, it is more likely to remain stable before either intensifying or weakening, whereas affected area displays a higher degree of phase retention, meaning that spatial patterns of drought coverage are more consistent over time. Such insights are crucial for early warning systems and adaptive drought management as they enable more accurate predictions of how a drought is likely to evolve in the following time steps.

4. Discussions

This study introduces a novel framework for analyzing spatiotemporal drought evolution, employing a three-curve model and a typology-based classification system derived from the dynamic behavior of drought characteristics. Our approach focuses on translating the complex outputs of 3D drought analysis into intuitive, actionable insights for drought monitoring and management. We found that Type II droughts, characterized by rapid expansion, prolonged persistence, and abrupt contraction, are the most prevalent in Northeast Brazil, a pattern attributed to the region's strong precipitation seasonality and the use of SPI-12.

The methodologies for analyzing spatiotemporal drought dynamics have evolved significantly. Classical approaches, such as Severity-Area-Duration (SAD) curves (Andreadis et al., 2005) offer aggregate statistics vital for climatological understanding and long-term planning. However, their aggregated nature often obscures intra-event dynamics critical for operational decision-making. For example, while a SAD curve provides the distribution of drought severity across different durations and areas for a population of droughts, it does not reveal the instantaneous phase (expansion, persistence, contraction) of a specific ongoing event. Our three-curve model explicitly addresses this gap by providing a diagnostic of how each drought event evolves, offering a process-oriented view not readily available from aggregate summaries.

More recent advancements, such as the 3D clustering algorithms developed by Herrera-Estrada et al. (2017) and Diaz et al. (2019), and the flexible DBSCAN-based approach by Cammalleri and Toreti (Cammalleri and Toreti, 2023), provide sophisticated means to track drought trajectories and characterize their statistical properties (e.g., displacement distances, preferential pathways). Banfi et al. (2024), for instance, apply a generalized 3D clustering approach and NATA curves to classify European droughts into broad seasonal categories. While these methods generate rigorous scientific descriptions, they often present complex analytical outputs that require significant expertise to interpret into actionable insights. Our innovation lies in translating these complex dynamics into a simplified three-curve representation and a directly applicable typology of drought evolution. This allows for a more intuitive grasp of drought behavior, enabling stakeholders to anticipate future patterns without needing to interpret a multitude of complex metrics or delve into statistical clustering results themselves. Furthermore, our approach's commitment to preserving all concurrent drought clusters, even upon splitting, offers a more comprehensive representation compared to some prior methods (e.g., Diaz et al., 2019; Herrera-Estrada et al., 2017) that might prioritize only the largest cluster, potentially overlooking critical localized events, especially relevant for regions with diverse climatic drivers.

The explicit aim of this framework is to provide structured and interpretable information that provide insightful understanding of drought evolutions that can be used in proactive preparedness planning. Traditional drought-monitoring systems such as the North American Drought Monitor (NADM) (https://droughtmonitor.unl.edu/) and Brazil’s Drought Monitor (https://monitordesecas.ana.gov.br/) serve primarily to track current drought conditions—mapping the spatial extent and intensity of drought in near-real-time (or at least on a monthly basis) in order to support operational decisions, based on hydro-meteorological indicators and verified with local institutions. By contrast, the methodology proposed here is not aimed at real-time operational monitoring, but rather at diagnosing how droughts evolve in time and space by focusing on intra-event dynamics (for example, expansion/shrinkage of the affected area and changes in severity within an event). In doing so, the tool can generate insights about typical behaviour patterns of drought events (e.g., how quickly severity increases, how the spatial footprint changes) that can inform proactive drought-management plans, rather than simply mapping current conditions for decision support. In other words, while existing monitors support situational awareness and trigger responses, our approach intends to support strategic planning by elucidating the regime of drought evolution—thereby enabling decision-makers to anticipate likely developments and craft management measures oriented to the typical progression of events rather than only to detected states.

While essential, these systems often lack a framework for systematically classifying and anticipating the evolutionary behavior of drought events. Our three-curve model and the derived typologies offer a diagnostic tool that can complement these systems by providing a deeper, process-oriented understanding of how a particular drought is likely to expand, persist, or contract. For example, by identifying a newly emerging drought as a "Type II" event (rapid expansion, long persistence, abrupt contraction), decision-makers can be better informed to anticipate prolonged impacts and allocate resources for extended periods, rather than reacting solely to current conditions. This enables proactive measures, such as adjusting water usage policies, implementing crop diversification strategies, or preparing emergency aid, well in advance of peak impacts. The ability to categorize and understand these distinct evolutionary pathways empowers managers to tailor response strategies more effectively, moving beyond purely reactive measures to more robust, anticipatory planning.

Despite its advancements, this study has limitations. First, the use of the CRU TS v4.05 dataset, with its 0.5° resolution, while providing a long historical record crucial for drought climatology, is acknowledged to be quite coarse for a region characterized by high spatial rainfall variability such as Northeast Brazil. This resolution inherently limits the capture of fine-scale meteorological phenomena and highly localized drought events, potentially smoothing out micro-climatic patterns that could be relevant for very specific local impacts. While this choice was pragmatic given the need for a consistent, long-term dataset to demonstrate our methodological framework, future applications would greatly benefit from higher-resolution precipitation data (e.g., from regional models or downscaled products) to enhance the precision of localized drought characterization. The reliance on SPI, though justified by data availability in NEB, means that the framework in this study primarily addresses meteorological drought, not directly incorporating the complexities of agricultural or hydrological droughts driven by temperature, evapotranspiration, or water storage changes. While the methodology is flexible enough to accommodate other indices, their direct application in this specific case study would require robust historical data, which are currently less available. Furthermore, the assignment of drought events to typologies was performed visually, which, while guided by theoretical models, introduces a subjective element. Although effective for this initial methodological demonstration, an automated classification method for typology assignment would enhance objectivity and scalability for large datasets. Lastly, while the framework provides insights into how droughts evolve, direct validation with decision-makers on its usability and impact on their management decisions is a necessary next step.

The proposed framework is highly transferable. Its core components—the 3D clustering algorithm, the three-curve model, and the typology definition—are independent of the specific drought index or geographical region. Any gridded time-series drought index can be used as input, allowing for application in diverse climatic zones and for various drought types (meteorological, agricultural, hydrological). This flexibility ensures that the methodology can be adapted to regions with different data availability and management priorities, making it a broadly applicable tool for enhancing drought monitoring worldwide.

Future work will focus on integrating additional climatic variables and testing alternative drought indices (e.g., SPEI, PDSI, soil moisture indicators) into the framework to provide a more comprehensive characterization of multi-faceted droughts. Efforts will also be directed towards developing automated classification algorithms for typology assignment to enhance objectivity and scalability. Crucially, direct engagement and validation with water managers and policymakers will be undertaken to refine the framework's practical utility and ensure its seamless integration into existing operational drought monitoring systems.

5. Conclusions

This study developed a spatio-temporal framework for drought classification, incorporating a 3D drought detection methodology, a three-curve model and the derived typologies of drought evolution to better understand how droughts evolve over time and space.

The application of the three-curve model—growth curve, state curve, and dynamics curve—proved to be a valuable tool for drought monitoring, allowing for a structured interpretation of drought expansion, persistence, and contraction phases. The transition matrix analysis further demonstrated that drought affected area extent tends to remain stable within each phase, while severity exhibits greater variability, suggesting that affected area may be a more reliable indicator for decision-making.

By analyzing affected area and severity, we identified four distinct drought evolution typologies, and the study revealed that Type II droughts—characterized by rapid expansion, long persistence, and abrupt contraction—are the most prevalent in the Noth of Northeast Brazil. The dominance of this drought type is likely influenced by the region's strong precipitation seasonality, where rainfall is concentrated within a short period, and by the use of SPI-12, which enhances the persistence of events in the analysis.

From a management perspective, these findings highlight the importance of early detection, long-term planning, and adaptive response strategies. Given the prevalence of rapid-expansion droughts, monitoring systems must be designed to detect early warning signs and enable proactive mitigation measures. Additionally, the prolonged persistence of droughts in the region reinforces the need for sustained water resource planning and agricultural adaptation policies.

This study provides a scientific foundation for improving drought monitoring and response strategies, offering a methodology that can be applied to other semi-arid regions facing similar climatic challenges. Future research should focus on integrating additional climatic variables, testing alternative drought indices, and expanding the analysis to other geographic contexts. By refining these tools, policymakers and researchers can enhance early warning systems, strengthen resilience-building measures, and mitigate the long-term socioeconomic and environmental impacts of droughts.

Code and data availability

The code and data used in this study are available upon request by emailing the corresponding author.

Author contributions

Conceptualization, methodology and validation, J.D.P.F., ABSE, and F.d.A.S.F.; formal analysis, investigation, writing—original draft preparation, J.D.P.F., F.d.A.S.F., ABSE, and E.S.P.R.M.; software, J.D.P.F and ABSE.; writing—review and editing, supervision: F.d.A.S.F., E.S.P.R.M. and T.M.d.C.S.

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Competing interests

The authors declare no conflict of interest.

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