Spatiotemporal Comparison of Drought Metrics over the Western United States

Adi Alexander Oleinick Stein

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Committee:

Bart Nijssen

Erkan Istanbulluoglu

John Abatzoglou

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University of Washington

Abstract

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Adi Alexander Oleinick Stein

Chair of the Supervisory Committee:

Bart Nijssen

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Drought definitions and drought metrics come in many different forms and it is not always clear which definition or metric is most useful for describing or forecasting drought impacts. Drought metrics range from those which only incorporate precipitation anomalies to more comprehensive measures such as the United States Drought Monitor (USDM), which incorporates on-the-ground observations of drought impacts to arrive at a consensus-based drought status. Here, we develop a method to compare drought metrics, as reported in the Climate Toolbox (https://climatetoolbox.org/), and investigate their level of agreement in assessing drought conditions in the western continental United States. We compare two drought metrics and evaluate how they spatially evolve over the two decade period from 2000 to 2021. Our drought metrics are the USDM and Standardized Precipitation Index (SPI) at 30 day (SPI30d) and 180 day (SPI180d) intervals. We propose utilizing contiguous drought area (CDA) analysis to extract drought tracks from a larger network of drought characterizations. CDA blobs are organized through a directed graph that we can pull out individual paths called threads. Threads are aligned between different metric graphs through spatio-temporal intersection. USDM drought characterizations were found to move slowly and be more persistent than SPI characterizations. Meanwhile SPI30d drought characterizations were fragmented and moved quickly with dynamic changes in size. SPI180d drought characterizations moved faster than USDM drought characterizations, but not as dynamically as SPI30d drought characterizations. Contiguous

areas between metrics were found to not necessarily result in the same drought evolution, yet we now have the means to compare evolutions. We found that the definition of drought used highly impacts the evolution observed.

1 Introduction

Drought is generally defined as a deficit of water for a given purpose over a certain time horizon (Kim et al. 2018, Corzo Perez et al 2011). That water deficit can be any part of the hydrologic cycle, (e.g., groundwater, streamflow, snow, rain), while purposes are stakeholder specific. Meteorological drought is caused by a lack of precipitation, impacting the rest of the hydrologic cycle. Businesses whose revenue depend on sufficient snow for skiing or water for rafting or tourism can experience socioeconomic drought when the water they depend on is lacking (Wlostowski et al. 2022). Socioeconomic drought can occur throughout a business's peak season, potentially cutting their revenue short. Hydrologic drought occurs when streamflow is below normal, which can affect a city or town water supply, (Wlostowski et al. 2022). Most aid from the United States Department of Agriculture (USDA) focuses on assisting farmers who need sufficient quantities and timings of water to sustain their crops, aiming to offset agricultural drought (USDA accessed 2023). Meanwhile flash drought occurs rapidly and can cause stress and kill plants even if the drought only lasts a week or two (Mo and Lettenmaier 2016). Flash droughts are named for their rapid onset and recovery, affecting systems that are sensitive to sudden changes such as specific crops. Forests and ecosystems might experience ecological drought when there is not enough water to support a healthy forest, leading to increased wildfire risk or pest susceptibility (Wlostowski et al. 2022, Parks et al. 2018). And yet, the answer to the question "are we in a drought?" depends on how we define drought and who is defining it. The United States Drought Monitor incorporates a wide variety of information into their discussion of drought (Svoboda 2002). The Standardized Precipitation Index (SPI) focuses on only one type of drought. No single metric can encompass all types of drought, especially as different types of drought exist at different timings and scales.

Drought can be analyzed as a static entity, using percentiles of a defined region being in drought to define impacts. However, doing so misses spatio-temporal nuances of drought (Andreadis et al 2005). Droughts compound across landscapes, leading to a cascade of impacts, making static analysis unrepresentative of their true nature (Brito 2021). Looking only at a static framework misses how drought is a dynamic entity that can originate in one region and branch out to impact many more. Contiguous Drought Analysis (CDA) was introduced by Andreadis et al. (2005) to track drought movement across a landscape. When needing to compare metrics to understand which best captures a desired drought flavor (Bumbaco and Mote 2010), static methods fail to capture spatial nuances. This becomes important when looking to characterize how a drought might evolve through a system, and in turn how policy and aid should best move forward in addressing drought.

Andreadis et al. (2005) introduced CDA that has then been expanded upon by others over the years. CDA is the process of following drought areas across space and time by following where drought areas are contiguous in time. Drought areas are referred to as clusters in Andreadis et al. (2005) as they track them across the United States. Llyod-Hughes (2011) utilizes CDA to visualize meteorological drought through a three-dimensional representation, analyzing its characteristics through how similar their shapes are. They found that large, persisting drought areas are due to many small drought areas being combined for short times, noting how feedback through the water cycle influences drought aggregation. Perez et al (2011) introduced non-contiguous drought area analysis (NCDA) in addition to CDA to apply global characterization of spatial event analysis while comparing multiple models to each other. The innovation of NCDA helps to contrast drought being represented as area-percentages versus clusters that is CDA. NCDA was found to be useful for global and regional assessment at defined hydro-climatic boundaries while CDA excelled in specific drought areas that go beyond those boundaries. Herrera-Estrada et al. (2017) also applied CDA to a global scale for the purpose of better understanding drought drivers for forecasting efforts. They found drought area and intensity thresholds that, when exceeded, had an increased probability of drought area growth and intensification before recovery. Konapala & Mishra (2017) represented hydroclimatic extremes through a network graph, introducing multiple thresholding of drought intensity to classify drought areas as clusters for CDA that had been focused on a drought intensity threshold previously. Using multiple thresholds, they found spatial hot spots for drought to be similar across thresholds. They also introduced orientation and distance metrics for CDA to understand spatio-temporal propagation of drought through a given region. Drought cluster orientation found lower drought intensity thresholds to "exhibit more clustered and spatially uniform orientations compared to a higher drought thresholds" (Konapala & Mishra 2017). Diaz et al (2020) focuses on improving centroid linkage, connecting drought clusters by centroid proximity rather than spatial contiguity, through a set of distance and area criteria, adding rotation to CDA characteristics. Their version of CDA, S-TRACK, found that minimum drought area is influential to drought path duration and severity and that duration and severity are not necessarily linked. Herrera-Estrada & Diffenbaugh (2020) used global spatiotemporal analysis to understand how ocean moisture deficits impact the development of drought over land, tracking drought beyond land masses. These landfalling droughts were found to account for approximately "16% of all large scale droughts over the continents" (Herrera-Estrada & Diffenbaugh 2020). Landfalling drought areas came from moisture anomalies evolving from large, high-pressure oceanic systems off the coast in a North America case study.

In an evolutionary framework that follows how drought moves through a region, we can understand why it might be beneficial to pick one metric over another. If one metric excels at capturing the onset of a flash drought through a valley, yet fails at capturing multi year droughts that impact the region, being able to characterize quantitatively how that metric performs becomes important.

Despite the need to compare how different metrics evolve in space and time, current literature only focuses on a singular drought metric. Tracking drought is possible visually by examining drought maps, yet quantitative characterizations of these tracks that are comparable across metrics are lacking. To address this, we developed a method to track individual drought events through time and compare these tracks quantitatively.

In this paper we demonstrate this method for tracking droughts and comparing drought tracks as defined according to different drought metrics. From this, we characterize the life cycle of droughts and how drought events compare across indicators.

2 Methodology

2.1 Drought Metric Background

In this paper, we focus on two metrics: the drought category as displayed in the United States Drought Monitor (USDM) and the Standardized Precipitation Index (SPI). Our method is not restricted to these two metrics and can be applied to droughts defined according to other metrics. USDM drought classifications are obtained from Bilotta (accessed 2023). SPI drought classifications are obtained through the Climate Toolbox (https://climatetoolbox.org/), a set of mapping/graphing tools that can be used to explore climate/hydrology data in real-time with comparisons to the past and insight into the future (sub-seasonal to seasonal forecasts and future projections) across the continental United States. USDM is a weekly descriptor of drought that considers various drought metrics to retroactively map drought (USDM accessed 2023). IThe USDM is designed by experts who take in a wide variety of information to draw drought boundaries and intensities across the United States. We use a gridded version from the climate toolbox collected from 2000-2022 at 0.025° spatial resolution (Bilotta, Accessed 2023). SPI is a statistical indicator of meteorological drought defined as a standardized anomaly of precipitation. It represents the difference in precipitation from the mean divided by the standard deviation of precipitation (Keyantash 2021)

$$SPI = (P - P^{*})/\sigma_{P}$$

Where P is precipitation, P^* is mean precipitation, and σ_P is standard deviation of precipitation over the time window. To address the right skew of precipitation, the above equation can be complicated by applying a transform instead of just a z-score. Computing SPI can be done over various time periods, from 14 days to 5 years, tracking excess and deficit of precipitation (Keyantash 2021). We retrieve SPI from the climate toolbox as well. In this paper we use SPI at 30 day (SPI30d) and 180 day (SPI180d) windows calculated every 5 days for the period 2000-2021 at a 0.0416° spatial resolution. Our study area focuses on everything west of longitude 105° in the continental United States (CONUS) (Figure 1). SPI is calculated as

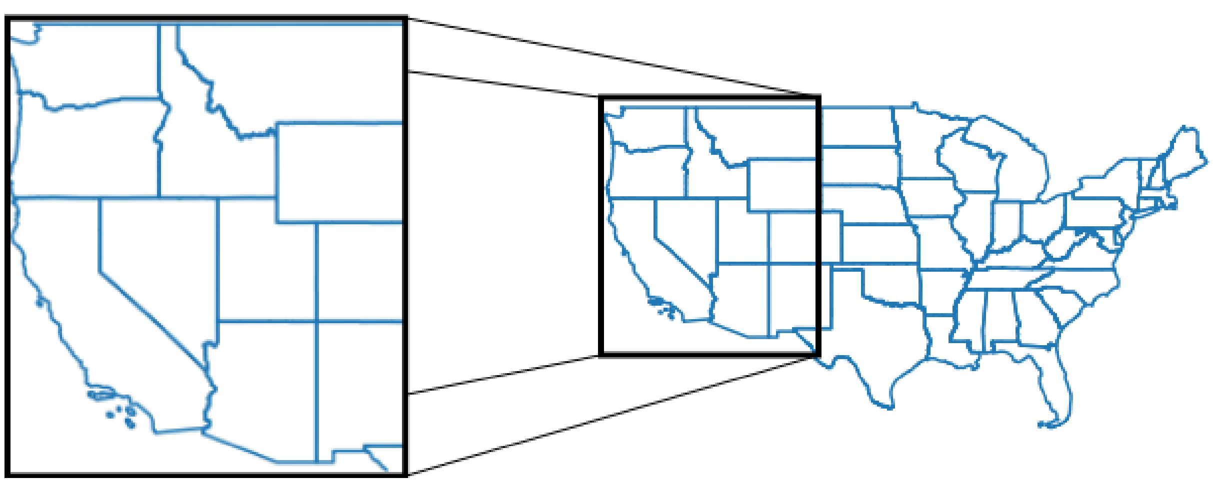


Figure 1: Study region of the western continental United States (map based on US Census Bureau accessed 2023).

2.2 Drought Metric Intercomparison

To compare each metric to each other, we need them:

- on a comparable scale/values, (e.g. a value of X in metric A corresponds to X in metric B)
- at the same spatial resolution if using raster data
- temporally aligned

We convert SPI into categories synonymous with the USDM, using guidelines for comparing other metrics to the USDM according to the National Drought Mitigation Center (NDMC) (Accessed 2023). Table 1 details this conversion.

Table 1: Categorization of metrics to drought severity synonymous with USDM (NDMC accessed 2023).

USDM Category	Standardized Precipitation Index (SPI)	Objective Drought Indicator Blends (percentiles)
Neutral / Wet	> -0.5	>30
D0	-0.5 to -0.7	21 to 30
D1	-0.8 to -1.2	11 to 20
D2	-1.3 to -1.5	6 to 10
D3	-1.6 to -1.9	3 to 5
D4	<= -2.0	0 to 2

When directly comparing metrics (section 2.5), each pairing is done independently of all other pairings, (e.g. pairing SPI30d and USDM would not be influenced by SPI180d). In a given pair, whichever metric has the finer spatial resolution is resampled using nearest neighbor resampling to the resolution of the coarser metric.

In aligning drought events temporally, we allow a difference of up to 1 week in the date stamp of the drought event. There are three usable schemes to temporally align metrics A and B for best match:

- **last-a**: match dates from metric B to the last dates of metric A available. Use if there is a reason to believe that metric A informs metric B
- **last-b**: match dates from metric A to the last dates of metric B available. Use if there is reason to believe that metric B informs metric A
- **nearest**: dates are paired by their nearest neighbors, dropping any dates that are not chosen in the process. Use if A and B do not inform each other.

With USDM as metric A and SPI as metric B, we used last-b as the method for aligning dates since SPI informs the USDM (Figure 2).

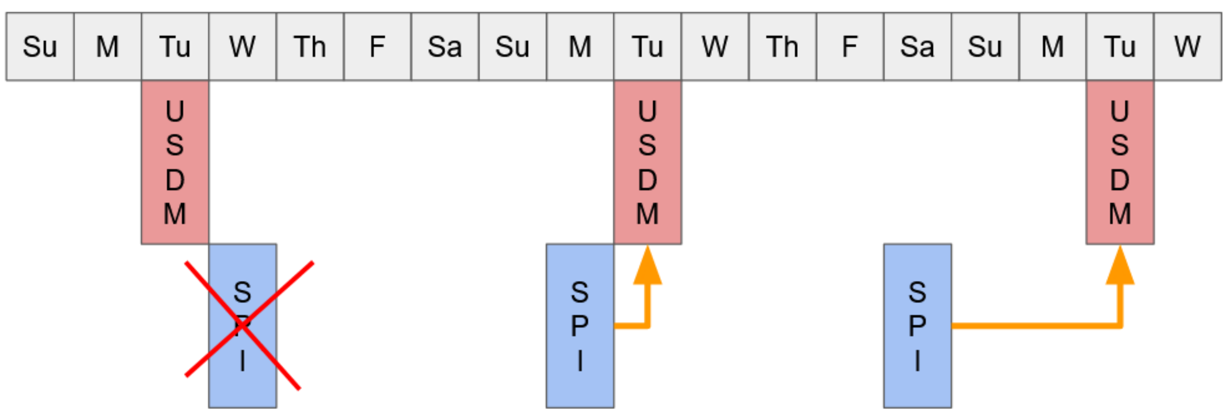


Figure 2: Temporal alignment of USDM, (weekly), and SPI (pentad), matching USDM to the last SPI date available. If multiple pentads occur within a weekly cycle, only the nearest pentad is chosen while the other is dropped.

2.3 Drought Network

Drought moves through a system similar to a storm or atmospheric river, it originates then evolves with diverging and converging substructures and eventually terminates (Guan and Walier 2019, Andreadis et al 2005). This paper's implementation of CDA allows any drought to be traced back to its origin and forward to its termination. We use a network graph to record this evolution, where each node in the graph is a drought at a specific time and space and edges trace the same drought through time. Two areas in drought are classified as part of the same drought if they spatially overlap. Using this framework, we can trace the entire evolution of a drought. We can then compare these traces for drought events identified by different drought metrics.

A **drought event** refers to an individual drought "blob" at a specific location and a specific moment in time These drought events are synonymous to the clusters defined in Andreadis et al. (2005). **Drought threads** are a series of sequential drought events defined by the same metric, as shown in Figure 3. We can think of threads as the evolution of a drought event over time, tracing where it goes/came from and how it changes spatially. Each drought event within the thread is a new time step, a snapshot of the evolution. A collection of drought threads over a time range and spatial extent is a **drought network** for a single metric.

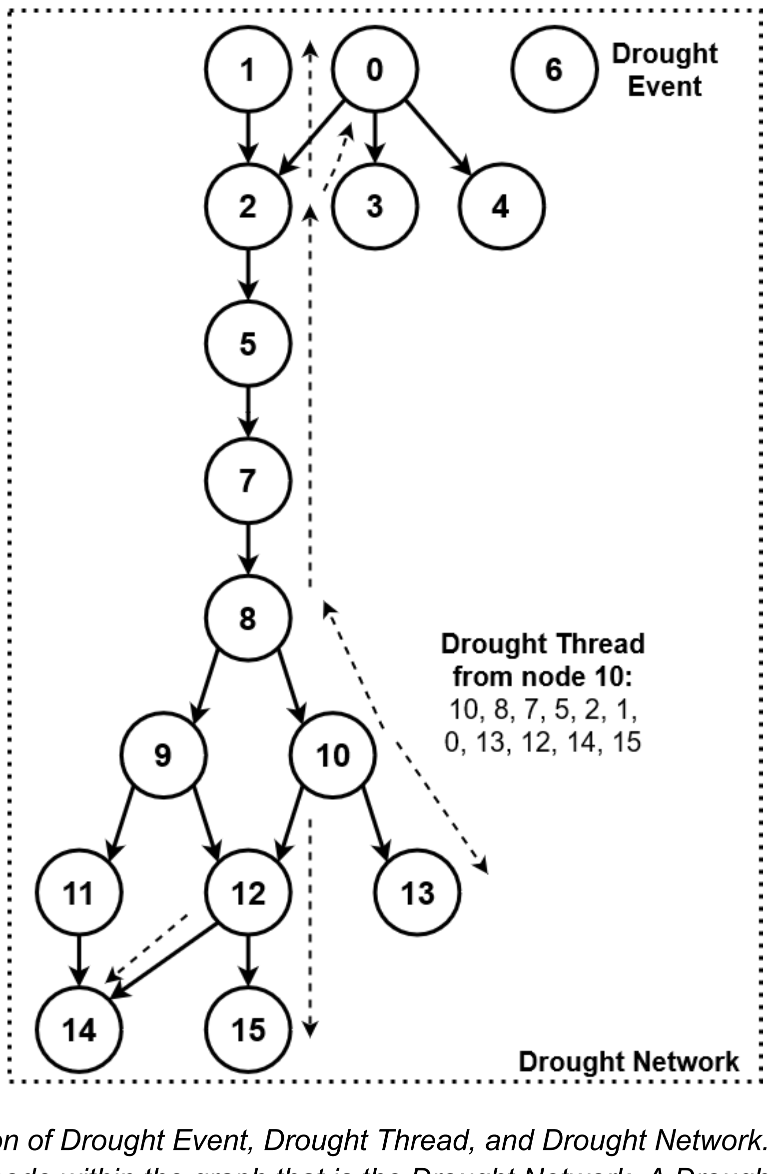
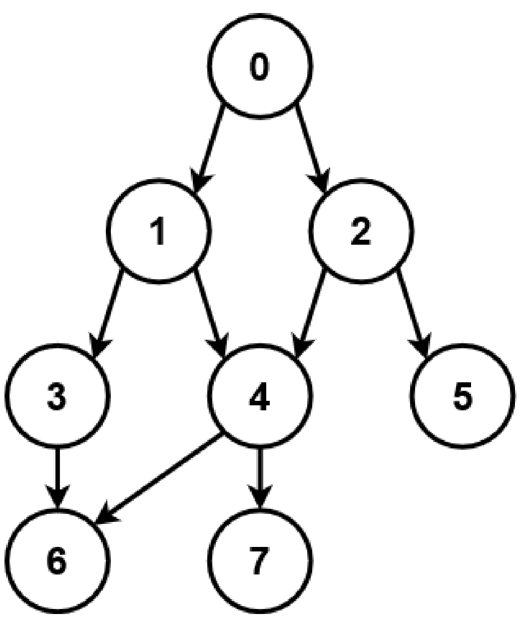


Figure 3: Illustration of Drought Event, Drought Thread, and Drought Network. A Drought Event refers to a single node within the graph that is the Drought Network. A Drought Thread is a path through the Drought Network that incorporates any splits and mergers in the direction of the path. A Drought Network can consist of multiple origin points, it is the collection of all Drought Events for a given definition of drought.

A drought network is a directed network graph that uses some definition of drought, as quantified according to a chosen drought metric, to represent drought evolution over space and time. A binary threshold based on the synonymous USDM categories converts each metric into a state of drought/no drought. Here, we used a threshold of D1 or greater as being in drought while D0 and neutral are no drought. Later section 3.1 we use a D2 threshold as well to have some variation in drought intensity thresholding. Then unique drought blobs are detected using blob identification software, clustering by recursively searching the 8 surrounding cells on a square grid, and are assigned a unique spatio-temporal id to identify them as a drought event. The drought event documents the time of the drought blob, its total area, a list of coordinates of the grid cells that compose it, which drought events come before it, and which drought events come after it. Each drought event is a node within a directed graph, where events that are contiguous in time are connected as part of a drought thread. A collection of these drought threads makes up a drought network. The drought network contains a name, when the network was created, the threshold used for the network, a list of origin nodes (drought events that have no precursor, they start a new drought thread), a list of all the nodes in the network, a copy of the binary three-dimensional array that the network was fed upon construction, and an adjacency dictionary. An adjacency dictionary is a key-value mapping where ids of nodes serve as keys while the values are the future node ids for that key, in contrast to an adjacency matrix that is commonly used which maps nodes and edges through a binary matrix, described further in Figure 4. Using an adjacency dictionary instead of an adjacency matrix improves performance time and enforces directionality in the graph. Creating this network allows for individual threads, which can also be thought of as evolutionary paths, to be extracted from the larger network by following the adjacency dictionary. This allows for analysis to be performed on a per-drought basis rather than mixing them all together in a standard drought map.



Adjacency Matrix

$$
\begin{array}{c}
 \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7
\end{array}
\begin{array}{c}
0\,1\,2\,3\,4\,5\,6\,7 \\
\begin{bmatrix}
0&1&1&0&0&0&0&0\\
1&0&0&1&1&0&0&0\\
1&0&0&0&1&1&0&0\\
0&1&0&0&0&0&1&0\\
0&1&1&0&0&0&0&1\\
0&0&1&0&0&0&0&0\\
0&0&0&1&0&0&0&0\\
0&0&0&0&1&0&0&0
\end{bmatrix}
\end{array}
$$

Adjacency Dictionary

0: [1, 2]
1: [3, 4]
2: [4, 5]
3: [6]
4: [7]
5: [ ]
6: [ ]
7: [ ]

Figure 4: Representation of an adjacency matrix versus an adjacency dictionary. Each row/column of an adjacency matrix corresponds to a node in the network graph. Everywhere there is a 1 in the adjacency matrix, there is a connection or edge formed between the two

nodes. Direction in the network graph can be specified in the adjacency matrix by only having rows signifying one direction and columns another, however no direction is indicated in this matrix. A downside of adjacency matrices is the large amount of space they can take up computationally when graphs get large. An adjacency dictionary on the other hand maps one node, left of the colon, to other nodes, right of the colon within the brackets. Adjacency dictionaries easily allow for direction to be specified by having the node to the left of the colon point in the direction of the nodes to the right of the colon. For example, "0: [1,2]" and "1: [3,4]" indicate that node 0 points to nodes 1 and 2, but node 2 does not point back at node 0, instead it points at nodes 3 and 4.

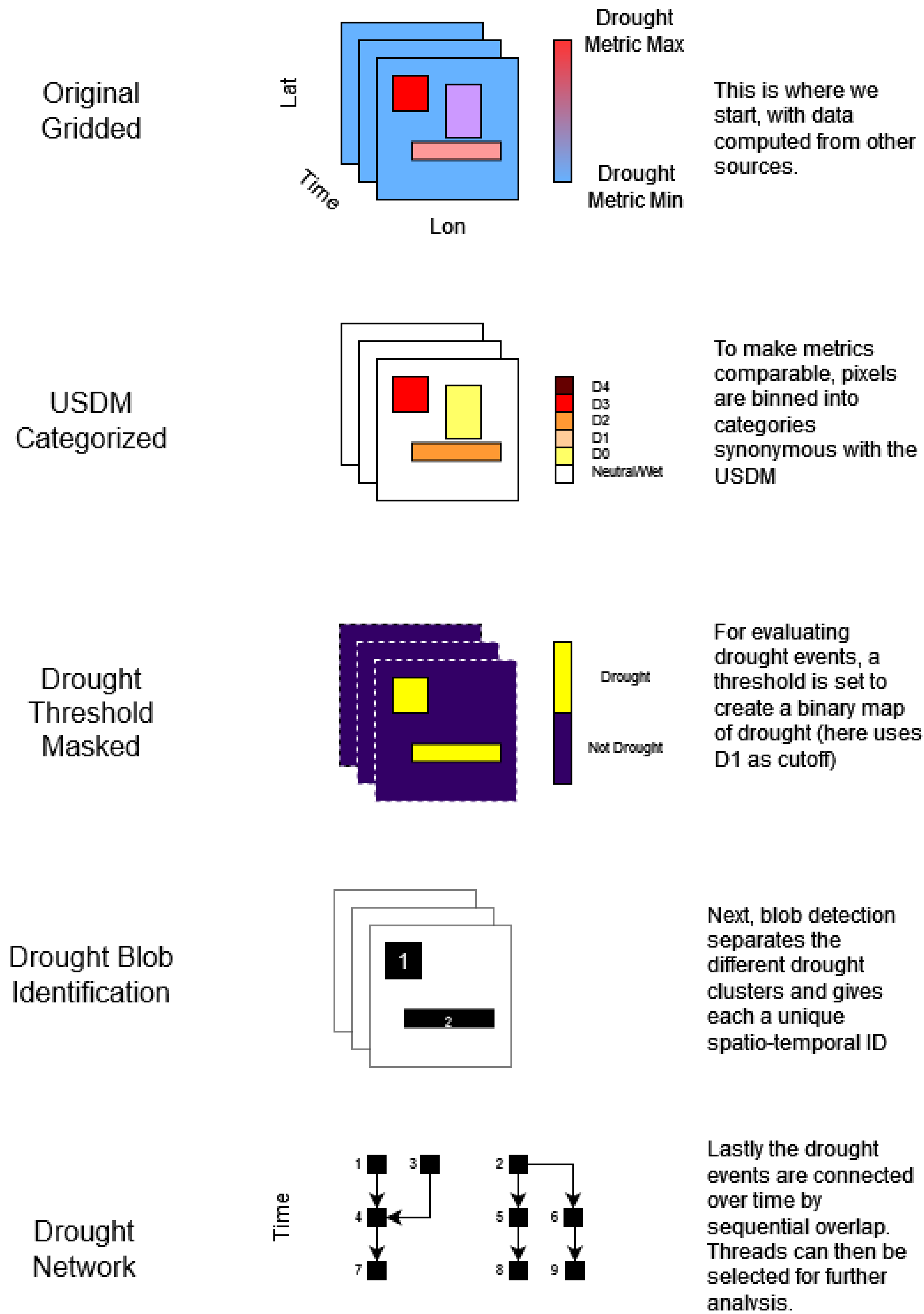


Figure 5: Workflow for constructing a Drought Network from gridded data. First the data is converted into USDM synonymous categories, as detailed in Table 1. Then a drought threshold is imposed to mask the data while each blob is identified and assigned a unique spatio-temporal id. Lastly, contiguous drought blobs are connected to form a directed graph.

Figure 5 explains our workflow taking gridded drought areas and turning them into drought networks. For example, if we have areas in drought areas A, B, and C with categories D0, D1, and D1+D2, respectively, then imposing a D1 threshold would retain only drought areas B and C. Next, an area filter is imposed to remove blobs smaller than 25,000 km^2. Each remaining drought area becomes a blob classified as a drought event with a unique spatio-temporal id, as Figure 5 shows. Finally, events that are 1 time step apart and spatially contiguous are defined as part of the same thread and are assigned to each other as their past and future nodes. In Figure 5, the network represents drought areas 1, 2, and 3 at the initial time step. The following time step we have 4, 5, and 6, where 4 is the merger of 1 and 3 while 5 and 6 are the split of 2. As drought events, nodes 1 and 3 would have 4 as their future while 4 would have 1 and 3 as its past, but would have no relation to 2. Similarly, 2 would have 5 and 6 as its future while 5 and 6 each have 2 as their past, with no relation to 1. If we were to collect all the origin events, we would then have nodes 1, 2 and 3.

Being able to construct a drought network for a metric enables a variety of features for CDA analysis. Individual threads can be isolated from the drought network for analysis, so that we can focus on a single drought event rather than multiple drought events that are evolving simultaneously in the study area (here the western US). Additionally, we can select specific time ranges for analysis. A drought network can also be converted back into a three-dimensional time-series mask for selecting droughts out of drought maps. Individual threads can be extracted to characterize drought evolution (section 2.4). Additionally, we can compare threads from different drought networks and compute similarity metrics (section 2.5).

2.4 Indirect Comparison: Drought Thread Characterization

Indirect comparison characterizes the evolution of a drought metric within its own network. This is done through several key characteristics often employed with CDA analysis: lifetime, total distance traveled, displacement from origin, average velocity, and change in size over time (referred to as similarity). To preserve areas and distances, the gridded dataset is transformed into an Albers Equal Area projection, EPSG:5070, before the drought network is constructed. Drought threads are retrieved by iterating through the adjacency dictionary from an origin node until a node is reached that has no future nodes. If the node the thread is being collected from is not an origin, then we also iterate through a reversed adjacency dictionary until reaching origin nodes. Centroids for each node are computed based on the list of coordinates of grid cells composing the node's drought area that each drought event contains. From each node in the thread, the following are gathered: x and y coordinates of the centroid of the current node, u and v the displacement between the current and future centroid, the time of the current node, the area of the current and future node, and the id of the current node.

Lifetime is computed by subtracting the latest time found (t_f) from the origin time (t_o).

$$Lifetime\ =\ t_f\ -\ t_0$$

Total distance traveled is computed as the sum of distances between centroids of contiguous nodes in the thread for n total nodes in the thread.

$$Total\ distance\ traveled\ = \sum_{i=0}^{n} \sqrt{(u_i)^2 + (v_i)^2}$$

Displacement from origin is the distance between the origin node centroid and the centroid of the node with the latest time in the thread.

$$Displacement\ = \sqrt{(x_o - (x_f + u_f))^2 + (y_o - (y_f + v_f))^2}$$

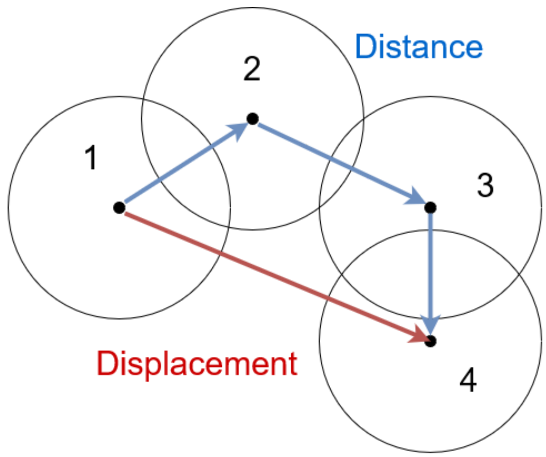


Figure 6: Illustration of distance and displacement. Distance incorporates the lengths between each set of centroids, while displacement is only the length between the first and last centroid.

Average velocity is computed by dividing total distance traveled by the lifetime of the thread.

$$Average\ thread\ velocity\ = \frac{total\ distance\ traveled}{lifetime}$$

Similarity provides a sense of how much change there is in the size of the drought area between time steps. How fast an area in drought changes in size impacts onset/recovery time. It is calculated as

$$Similarity\ = \ minimum(\frac{future\ node\ area}{current\ node\ area}, \frac{current\ node\ area}{future\ node\ area})$$

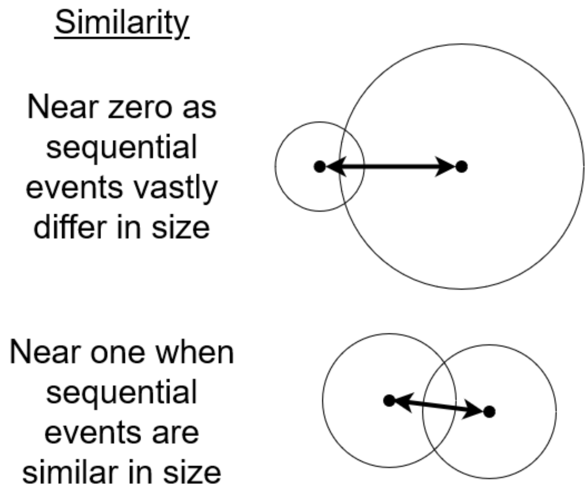


Figure 7: Similarity represents how similar in size two drought area blobs are. Values near zero when sequential events vastly differ in size. Values near one when sequential events are similar in size.

These characteristics are computed then grouped into drought lifetime categories, (0-30, 30-60, 60-90, 90-180, 180-365, 365-730, and 730-1825 days). Droughts exceeding 1825 days (5 years) are not included because they can run up to the length of the entire record, which would be a persistence artifact, not representative of realistic drought conditions. Drought lifetime categories are used to group droughts of similar behavior to each other. A drought that lives longer will have more opportunity to move a greater distance than one with a shorter lifetime. Without the categories, short-term and long-term droughts would be hidden by medium-term droughts.

Being able to individually characterize drought provides the first of two means of comparing drought metrics. Constructing characterization profiles, quantitative descriptors of how a drought metric generally behaves, of drought metrics provides a means for indirect comparison between two metrics. Distance traveled and displacement provide a sense of how typical movement is and to what scale. Mean speed provides an understanding of how quickly that movement occurs. Lifetime provides not only a category from which to organize all other characteristics, but also depicts the typical and atypical duration of droughts. While all these characteristics are fairly familiar to CDA analysis, similarity is not often used and provides a sense of how much droughts change in size throughout their lifespan. Similarity is computed over the lifetime of a drought by computing it between every node and its future node, then aggregating based on a statistic to get a singular value. A drought metric with high similarity, near one, does not change much in size between time intervals and may be considered a slowly evolving metric. Conversely, a drought metric with low similarity, near zero, changes drastically between time steps as a dynamic metric.

In extracting a drought thread, collecting all the nodes that lead to/from an event to capture the evolution of that event, two more filters are imposed to reduce noise: a continuation threshold and a singular-termination point requirement. Both of these techniques help to follow the dominant path instead of a smaller off-shoot track that may not be characteristic of the drought thread. A drought thread can split and various off-shoot threads can result, so any path that results in 80% or more reduction in the area of the drought is considered not part of the dominant path and cut off from the thread's statistics.

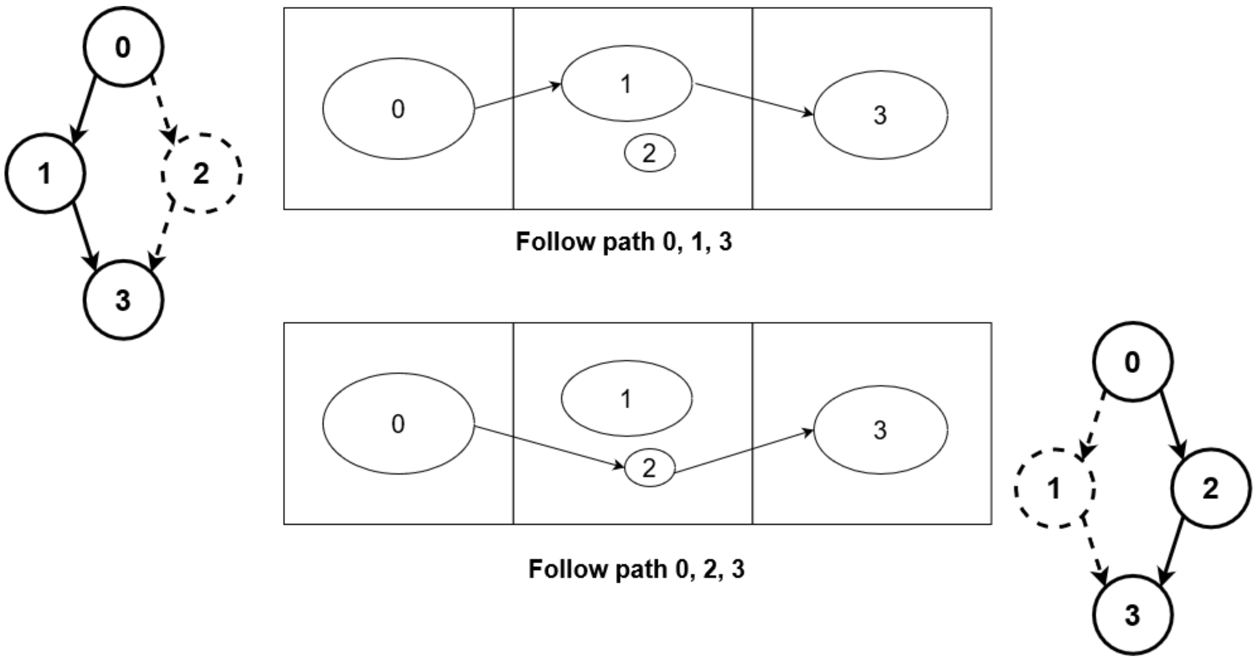


Figure 8: Description of need for singular-termination point requirement. If we are gathering all the possible paths a drought thread can go, then in this plot we have two options: thread 0, 1, 3 and thread 0, 2, 3. When computing statistics on a group of threads to construct a characterization profile, including both threads would result in drought event 3 being represented twice in the list when it occurs only once in reality. This biases the statistics towards overrepresenting large events (3) that are the product of smaller events (2) being consumed by other large events (1) when they were just an offshoot from the same event (0). Our solution is to follow the pather with the greatest cumulative area, which would be path 0, 1, 3 here.

Similarly, small events can merge with large events, creating an appearance of threads with multiple large events in their path that in reality are the same large event. Large events consuming small events and resulting in their overrepresentation is handled through the singular-termination point requirement, where only one thread can exist with each termination point. This dominant, singular thread, is chosen as the thread with the greatest cumulative area over its entire lifespan. Since drought threads only progress one direction in time at a time, this means that an event that splits off and then joins later loses the time step it was away from the large drought event, reducing its cumulative area. Only the thread that follows the path with the greater area each time will end up with the largest cumulative area and therefore be assigned that termination point, dropping all other threads during analysis.

2.5 Direct Comparison

Direct comparison involves overlapping drought networks as defined according to two different drought metrics, e.g., USDM and SPI30d. By searching for maximum overlap between two threads based on two different metrics overlap, we can pair threads and then compare how closely their evolution aligns. This provides a sense of how well two metrics capture the same drought (by being in the same location at the same time). Inversely, we can compute for all time the area in drought that is unique to each metric.

To overlap two threads, first a node is selected from one network to search for spatially intersecting nodes at the same time in another network (Figure 9a). Then for each set of nodes, per network, their path is traced forwards and backwards in time until reaching terminations and origin points respectively. This gathers all the nodes that are part of the thread that constitutes that drought event node's evolution. With all the nodes in the thread gathered, intersection among temporally consistent node coordinates is checked and intersecting nodes are recorded.

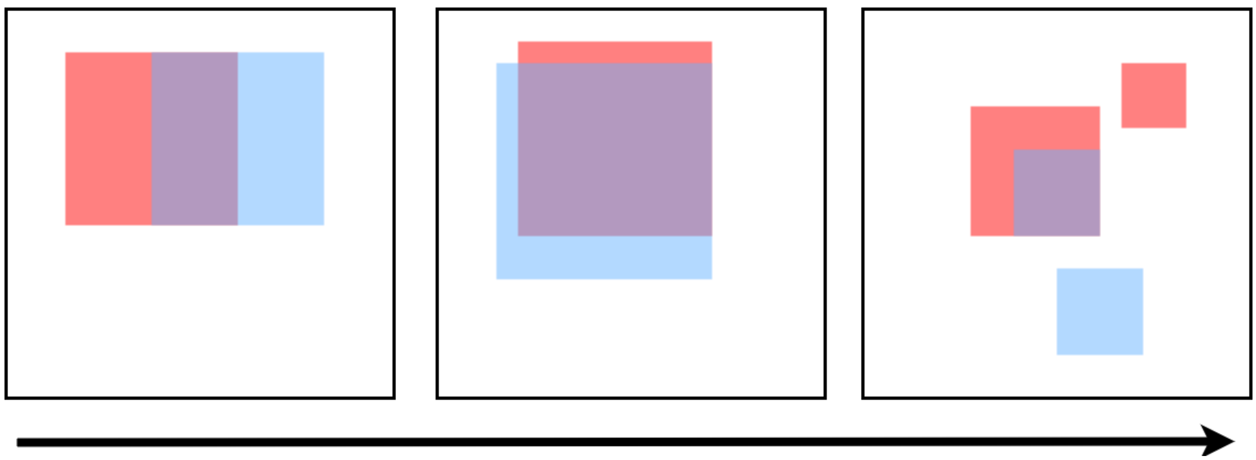


Figure 9a: An example of overlapping two threads between metrics A (red) and B (blue). If we first find the intersection in the middle panel, then we would trace backwards to the left panel and forwards to the right panel. Since all three of these panels have intersections, we would gather the nodes for all three and label them with each time period.

Computing alignment area (AA) between two networks uses the overlapped nodes by counting how many grid cells the two overlapped nodes have in common for each time step, then multiplying by the area of each grid cell (Figure 9b). This calculation is simplified by using Albers Equal Area projection EPSG:5070 so that each grid cell has the same area. AA results in being the area shared between two different drought networks.

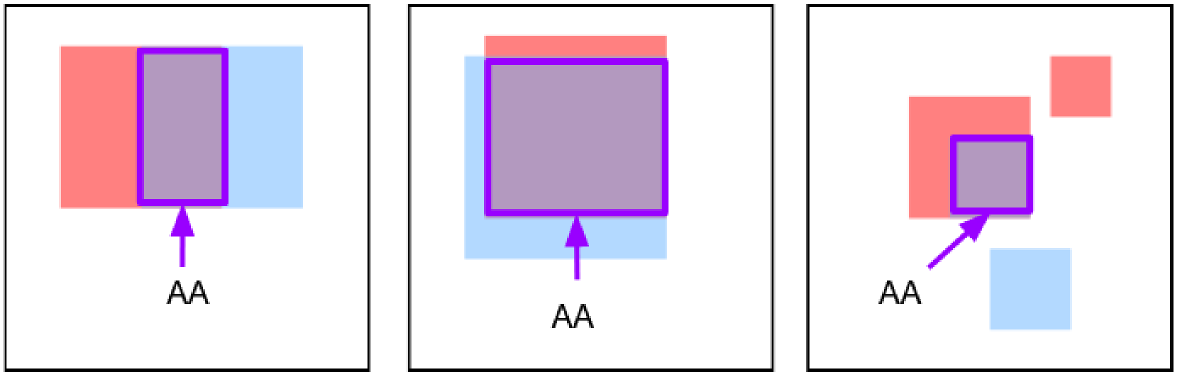


Figure 9b: Illustration of Alignment Area (AA) between two metrics, A in red and B in blue. AA is the common area shared between the two metrics, resulting in a purple when overlapped. Note that AA_A = AA_B always.

Computing disagreement area (DA) counts the area of the nodes not in the list of overlapping nodes to determine how much area is unique to each drought metric (Figure 9c). DA only includes areas unique to each metric, it does not include the non-overlapping area in the list of overlapping nodes.

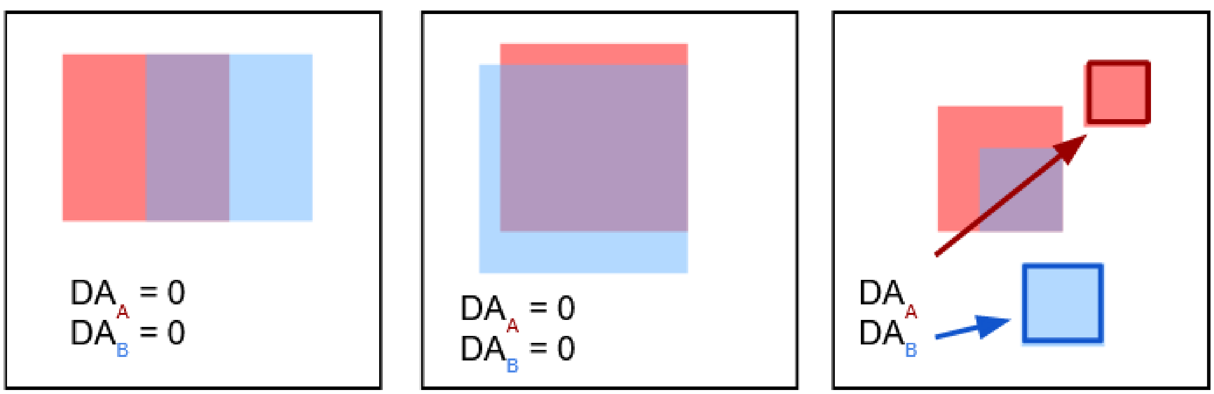


Figure 9c: Illustration of Disagreement Area (DA) between two metrics, A in red and B in blue. For the left and center panel, there is only overlapping area, no unique area between the two metrics, so DA for both is zero. In the right panel however, we see a region of A and a region of B that are non-contiguous with the other metric's area, resulting in a non-zero DA for both. DA_A is not necessarily equivalent to DA_B because they focus on unique areas, not shared areas like AA.

3 Results & Discussion

This section covers our findings using methodologies from section 2. Section 3.1 covers indirect comparison, constructing a characterization profile of a drought according to sections 2.3 and 2.4. In section 3.2 we delve into directly comparing drought networks for the USDM, SPI30d, and SPI180d through alignment and disagreement area covered in section 2.5. Then we transition into a discussion of the problems and challenges faced in our research in section 3.3.

3.1 Indirect Comparison: Total-Area & Metric Character Profiles

Here we examine the total area and metric character profiles, starting with total-areas for USDM, SPI30d, and SPI180d. We select out three times from each total-area time series to demonstrate what the map of the study region looks like according to that measure as an example.

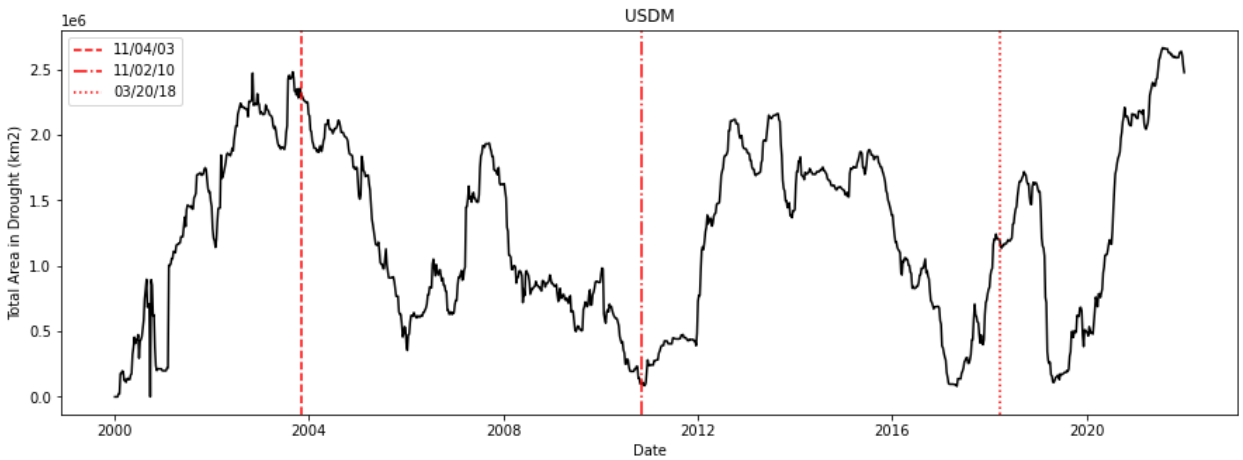


Figure 10a: Total area in drought for USDM.

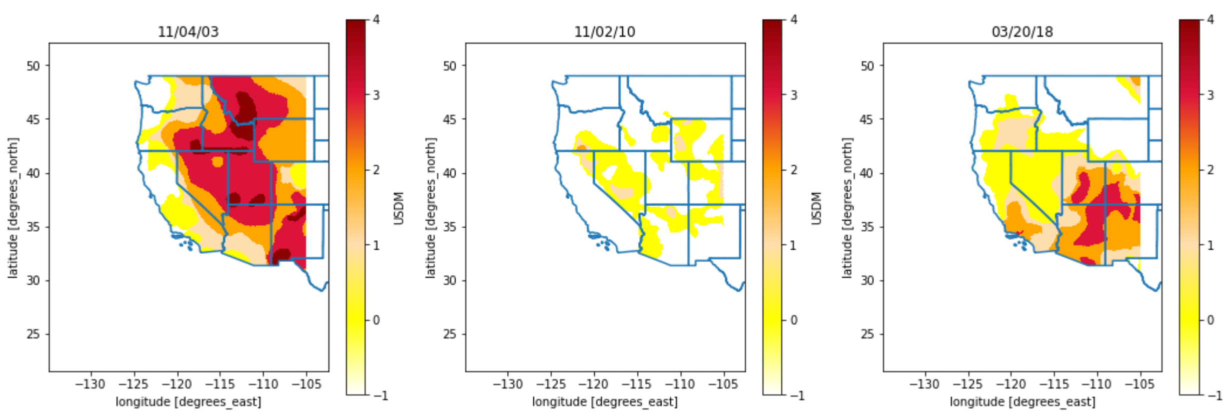


Figure 10b: Select USDM maps corresponding to the dashed vertical red lines in Figure 10a.

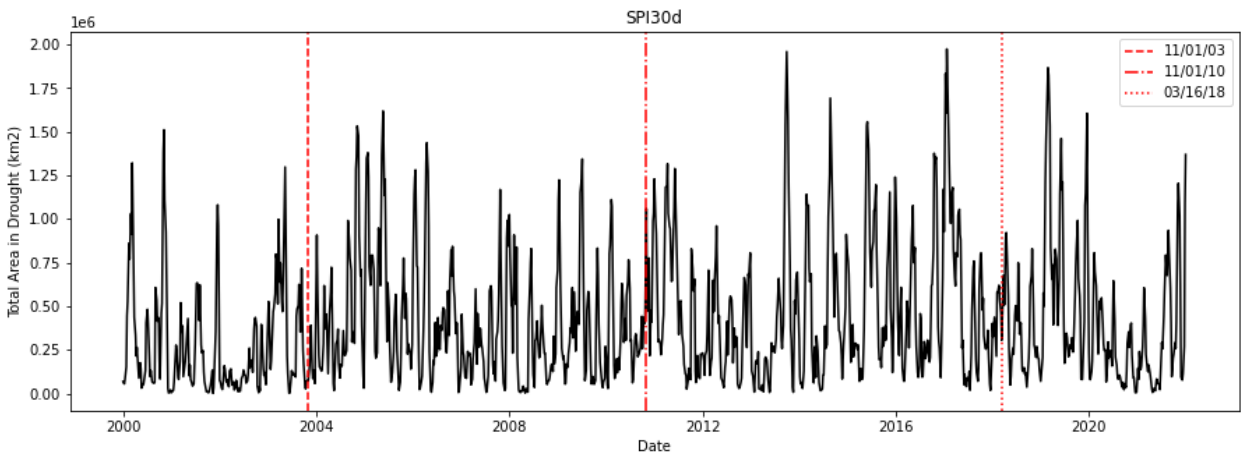


Figure 10c: Total area in drought for SPI30d.

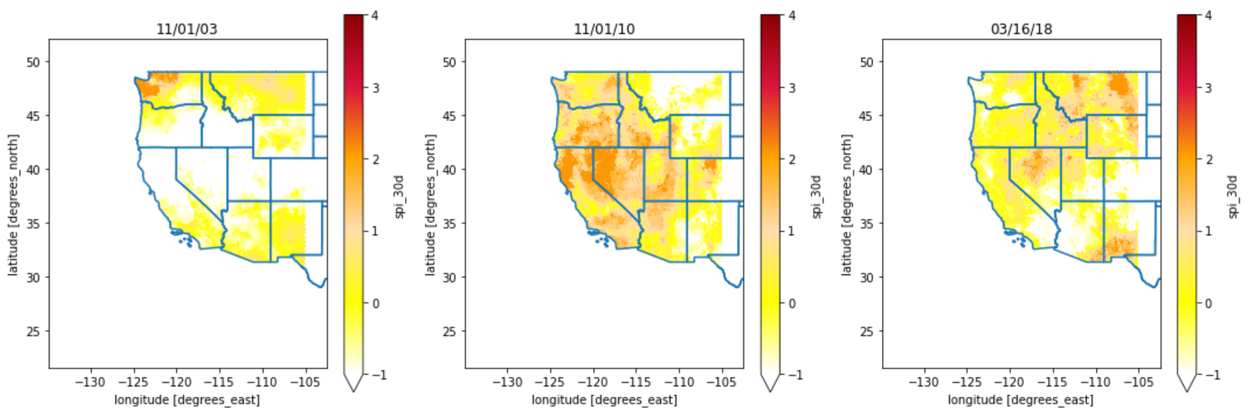


Figure 10d: Select maps for SPI30d corresponding to the dashed vertical red lines in Figure 10c.

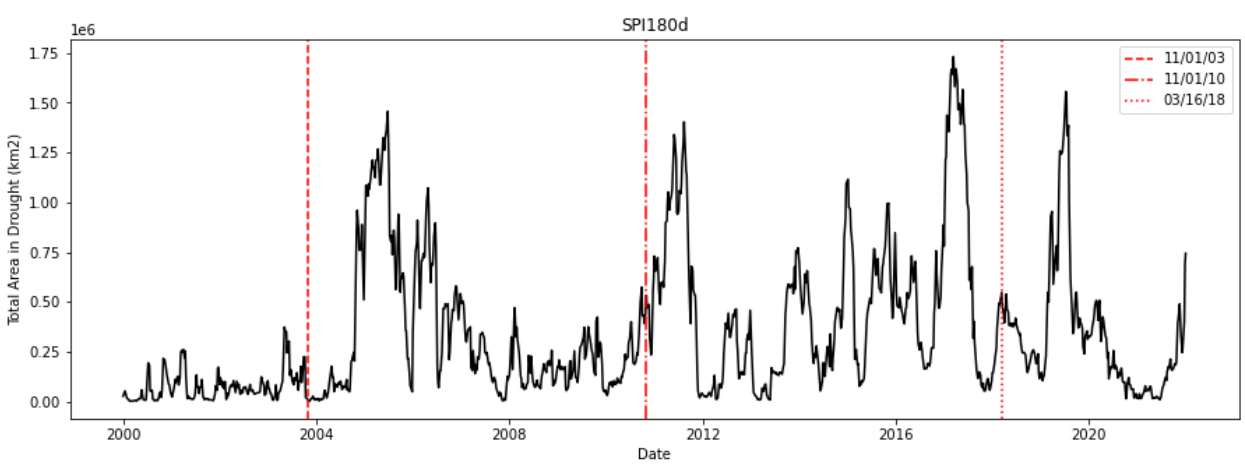


Figure 10e: Total area in drought for SPI180d.

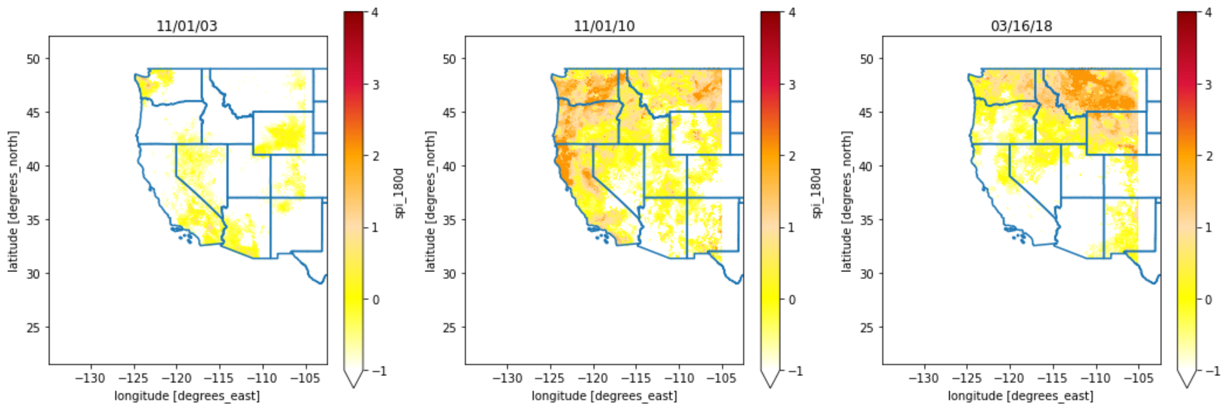


Figure 10f: Select maps for SPI180d corresponding to the dashed vertical red lines in Figure 10e.

Figure 10a-f: Plots a, c, and e are total drought area for USDM, SPI30d, SPI180d respectively. Plots b, d, and f meanwhile are snapshots from their corresponding time series that precede them, denoted by red lines in a, c, and e. The snapshots between all the plots are all at the same paired time (section 2.2), which is 11/04/2003, 11/02/2010, and 03/20/2018 for USDM in a and b and 11/03/2023, 11/01/20210, and 03/16/2018 for SPI30d in c and d and SPI180d in e and f.

In Figure 10a we can visualize how USDM is composed of large, singular drought events. Figure 10b shows that even at some of its lowest total area in the middle figure, that USDM drought area is still connected through a simply lower intensity threshold, (where everything is connected by yellow that is filtered out as D1 is tan). SPI30d in Figure 10c meanwhile is much more dynamic and noisy than USDM. The drought areas in FIgure 10d are much more fragmented than USDM drought area's smoothly drawn boundaries. Figure 10e shows SPI180d having not nearly as much noise as SPI30d, but still much less persistent than USDM. Comparing this to Figure 10f, SPI180d retains the fragmentation of SPI30d.

Next we delve into characterization profiles for USDM, SPI30d, and SPI180d at D1 and D2 drought area thresholds. Mean and maximum values are presented to provide a sense of the average and extreme values for characteristics within the handful of drought threads found for each lifetime category. Standard deviation is additionally provided for similarity to understand how much values vary around the mean provided. Due to the low number of total threads found per lifetime category in USDM and longer lifetimes for SPI, these profiles are represented as tables rather than plots to avoid creating misleading generalizations. Note how these values differ more across metrics than between D1 and D2 thresholds.

Table 2a : USDM character profile with D1 threshold.

Days	Lifetime (days)		Distance (km)		Displacement (km)		Average Thread Velocity (km/d)		Similarity (-)			Count
	Mea	Max	Mean	Max	Mean	Max	Mean	Max	Mean	Min	Std	

	n											
0-30	21	28	41	106	41	106	3	8	0.940	0.878	0.069	4
30-60	47	56	55	130	13	24	1	3	0.953	0.885	0.059	3
60-90	65	70	96	262	57	144	2	4	0.930	0.840	0.080	3
90-180	120	161	544	1209	194	421	4	10	0.885	0.779	0.057	8
180-365	252	273	737	1427	41	49	3	5	0.931	0.983	0.073	2

Table 2b: USDM character profile with D2 threshold.

Days	Lifetime (days)		Distance (km)		Displacement (km)		Average Thread Velocity (km/d)		Similarity (-)			Count
	Mean	Max	Mean	Max	Mean	Max	Mean	Max	Mean	Min	Std	
0-30	22	28	33	102	24	67	2	10	0.929	0.796	0.094	6
30-60	41	56	64	166	45	87	2	4	0.937	0.884	0.057	5
60-90	72	77	88	191	51	89	1	3	0.935	0.867	0.052	4
90-180	98	105	226	390	117	170	2	4	0.919	0.883	0.037	3
180-365	261	294	293	608	52	71	1	3	0.951	0.907	0.038	3
365-730	528	581	2539	2961	277	389	5	6	0.921	0.908	0.018	2
730-1825	847	854	3328	3726	902	1110	4	4	0.928	0.919	0.013	2

Table 3a: SPI 30-day character profile with D1 threshold.

Days	Lifetime (days)		Distance (km)		Displacement (km)		Average Thread Velocity (km/d)		Similarity (km2/km2)			Count
	Mean	Max	Mean	Max	Mean	Max	Mean	Max	Mean	Min	Std	
0-30	16	28	459	2729	266	1237	29	110	0.644	0.246	0.157	151
30-60	44	56	1433	2692	592	1271	33	64	0.609	0.425	0.094	28
60-90	72	84	2552	4716	704	1615	36	68	0.603	0.45	0.067	17
90-180	110	161	4498	7204	696	1272	40	53	0.597	0.51	0.069	7

Table 3b: SPI 30-day character profile with D2 threshold.

Days	Lifetime (days)	Distance (km)	Displacement (km)	Average Thread Velocity (km/d)	Similarity (km2/km2)	Count

	Mean	Max	Mean	Max	Mean	Max	Mean	Max	Mean	Min	Std	
0-30	14	28	357	2311	172	811	24	147	0.645	0.303	0.148	73
30-60	42	56	1582	2585	657	977	39	74	0.613	0.482	0.125	3

Table 4a: SPI 180-day character profile with D1 threshold.

Days	Lifetime (days)		Distance (km)		Displacement (km)		Average Thread Velocity (km/d)		Similarity (km2/km2)			Count
	Mean	Max	Mean	Max	Mean	Max	Mean	Max	Mean	Min	Std	
0-30	15	28	131	781	65	537	8	37	0.766	0.475	0.113	56
30-60	44	56	266	848	116	365	6	17	0.772	0.513	0.102	15
60-90	75	80	946	2840	154	538	12	34	0.743	0.531	0.108	8
90-180	129	119	1205	5533	192	806	9	33	0.789	0.585	0.085	17
180-365	271	245	2441	4042	482	725	8	11	0.816	0.802	0.016	3
365-730	410	483	5421	8289	823	1289	13	22	0.799	0.766	0.025	6

Table 4b: SPI 180-day character profile with D2 threshold.

Days	Lifetime (days)		Distance (km)		Displacement (km)		Average Thread Velocity (km/d)		Similarity (km2/km2)			Count
	Mean	Max	Mean	Max	Mean	Max	Mean	Max	Mean	Min	Std	
0-30	14	28	136	657	74	279	11	47	0.764	0.47	0.123	18
30-60	38	42	286	428	110	152	7	10	0.748	0.686	0.088	2
60-90	77	84	373	569	267	459	5	8	0.82	0.762	0.057	3
90-180	123	168	1172	1940	162	448	10	13	0.742	0.657	0.053	5
180-365	191	189	2726	5897	621	1199	14	31	0.786	0.713	0.073	3

USDM moves the slowest, travels the least, and changes in size the least between time steps compared to SPI30d and SPI180d. Yet we observe from Figure 10 that USDM has the largest and most persistent areas in drought. From this information, we can conclude that USDM characterizes drought as occupying large areas slow in onset and recovery, persisting by being slower to change. SPI30d characterizes drought as much more dynamic however, moving the fastest and furthest of all three metrics. When returning to Figure 10, Table 3a contextualizes the smaller areas that SPI30d occupies as still covering large amounts of ground despite their short lives. Meanwhile SPI180d drought characterization straddles the other two metrics in character, moving notably faster than USDM drought characterization but still much slower than the SPI30d drought characterization. SPI180d drought characterization still has much quicker onset and recovery than USDM drought characterizations, as shown in Figure 10 and furthered by its lower similarity values.

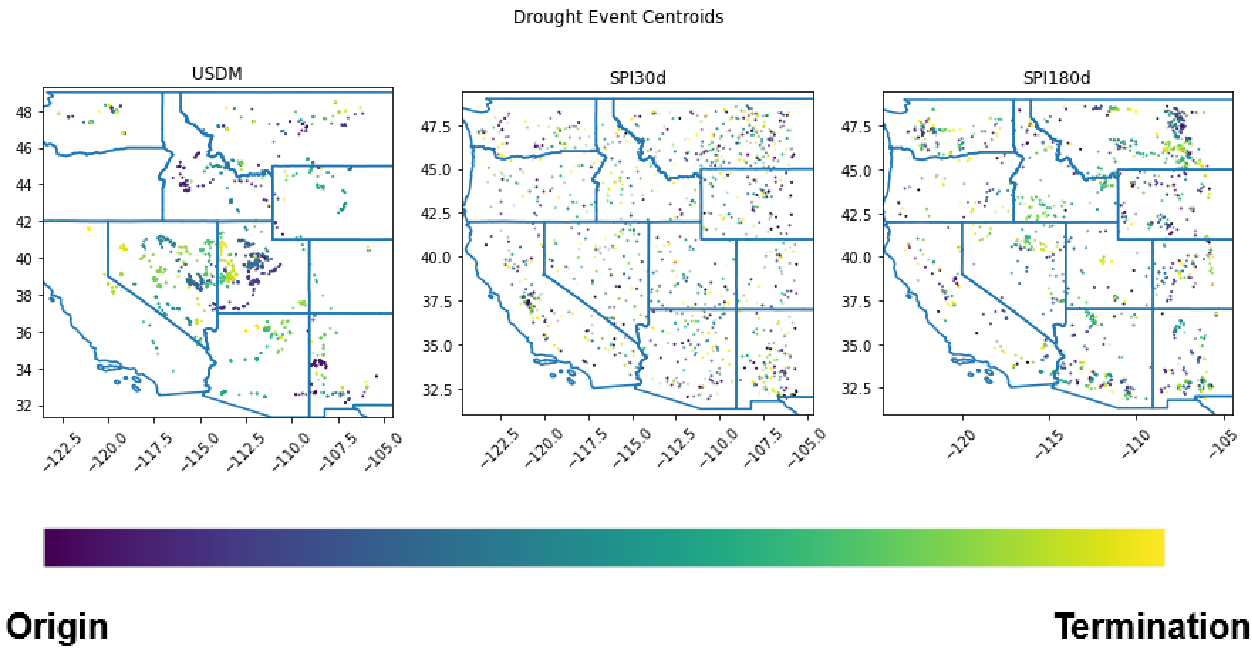


Figure 11a-c (left to right): Drought thread centroids for all events during the study period, where purple indicates an origin point and yellow indicates a termination point.

We can plot the centroids of our drought threads for each metric. Figure 11 presents USDM as favoring the center of our region much more than either SPI metric. All figures are impacted by boundary effects where the drought moves beyond or extends outside our study region, e.g., resulting in lines of centroids along the northern Montana border. SPI30d largely does not contain any grouping tendencies aside from California excluding a southeastern path and favoring the northern part of the state. SPI180d has notably more groupings than SPI30d, but not nearly as strong as the USDM.

3.2 Direct Comparison: AA & DA

Here we delve into two examples of direct comparison between USDM, SPI30d, and SPI180d. The first traces forward and backward in time through a thread that intersects on January 20th, 2017. Second we trace forward and backward through time on a thread that intersects on July 14th, 2015. The first was chosen as the thread that contained the largest SPI30d drought area in our record, while the second is motivated by the pacific northwest drought in 2015.

From these examples, we can evaluate how well overlapping between metrics represents similar droughts being captured. With the spatial maps, we can interpret relationships between AA, DA, and total area to understand how evolutions differ across drought metrics.

3.2.1 Thread from January 20th, 2017

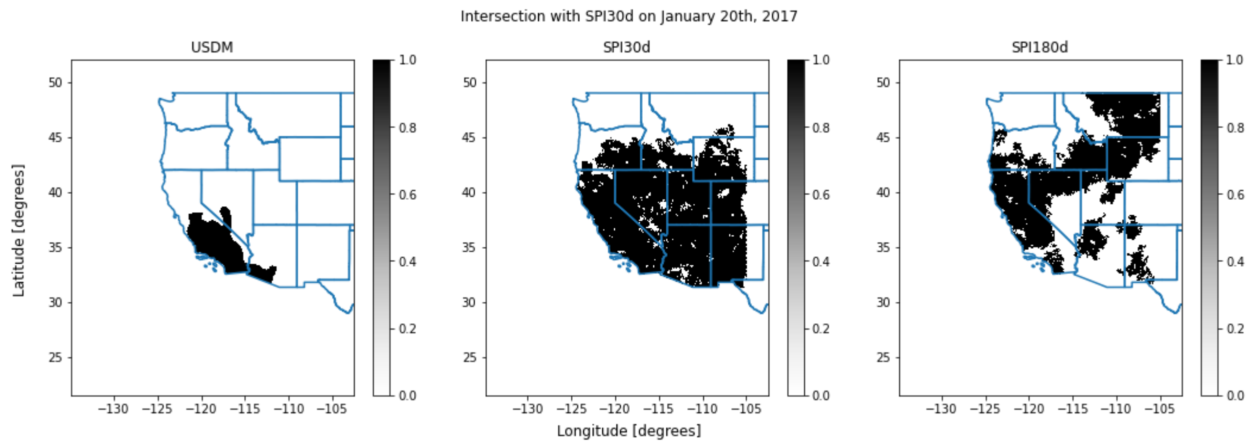


Figure 12: Intersection with SPI30d on January 20th, 2017, with USDM and SPI180d. Note that this occurs for USDM on January 21st instead of the 20th, but is considered comparable from section 2.2.

This example showcases drought from USDM, SPI30d, and SPI180d that all intersect spatially on January 20th, 2017 (Figure 12). Note how SPI manifests in similar evolution in the 30 day and 180 day intervals, but USDM, despite intersecting with SPI, shows a different drought evolution. USDM largely focuses on California while SPI focuses on the majority of the western US. This showcases how difficult it is to pick the same drought between two metrics, discussed further in section 3.3.3.

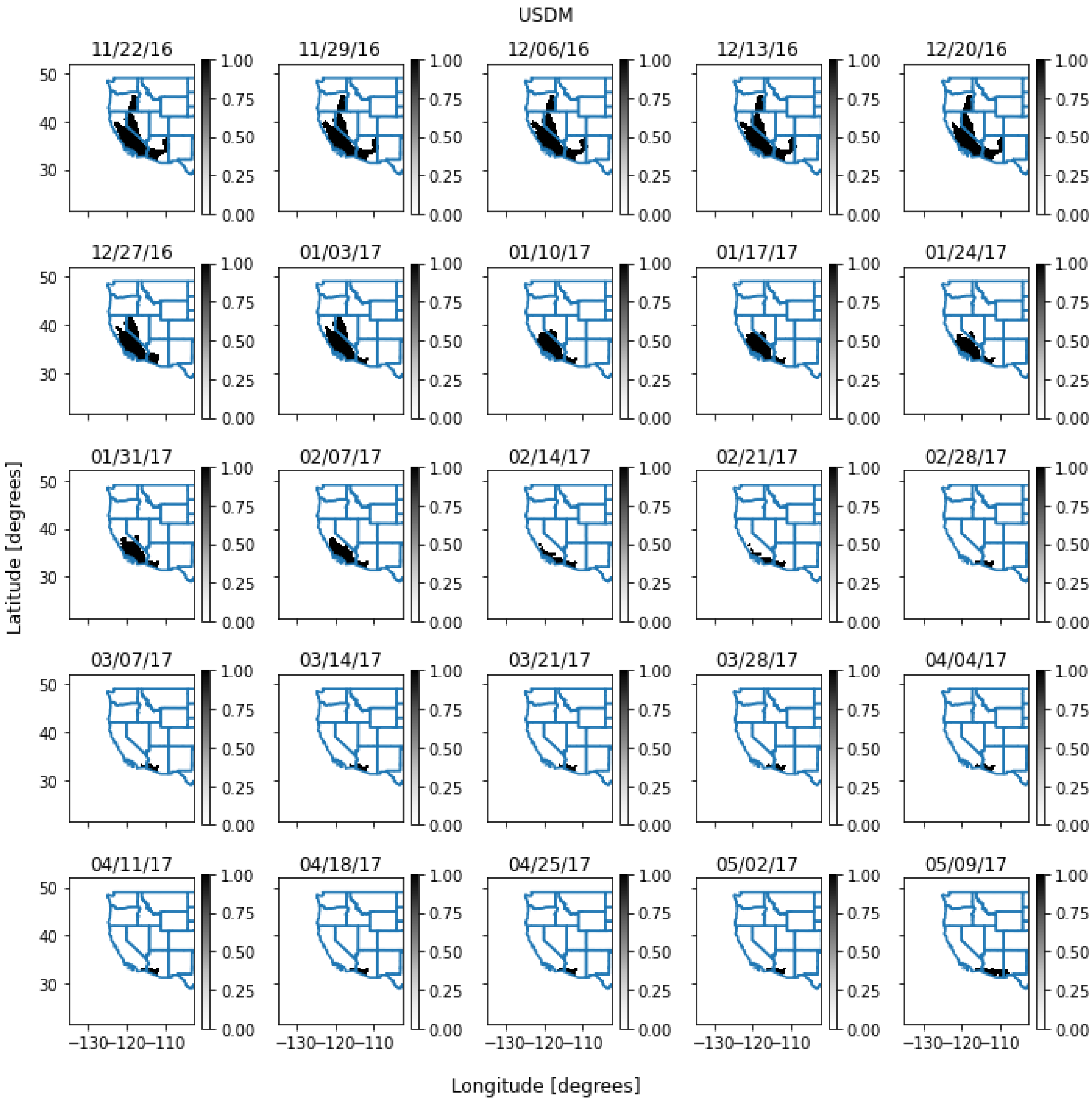


Figure 13a: Spatial plots for the USDM drought thread traced from January 20th, 2017.

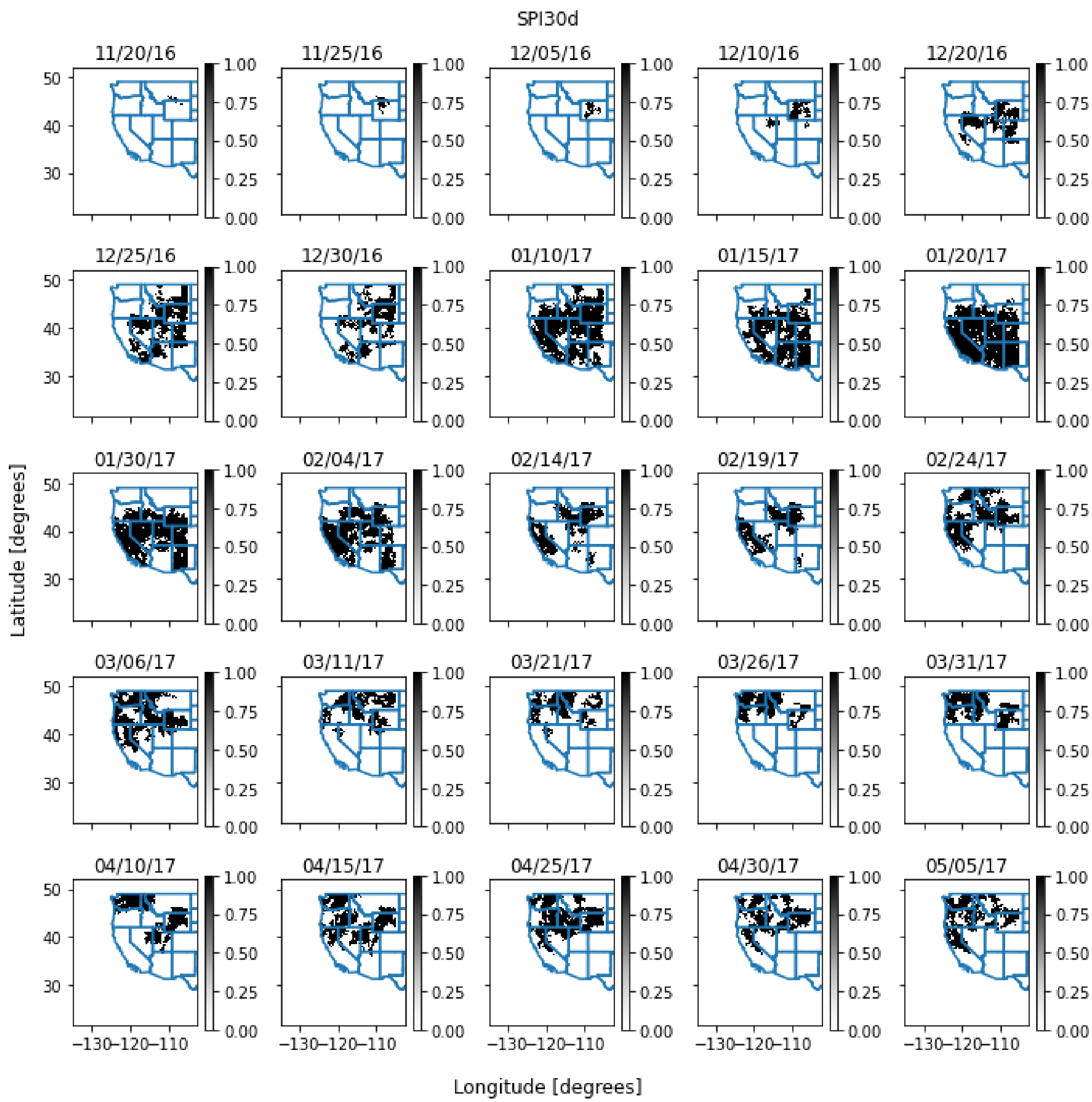


Figure 13b: Spatial plots for the SPI30d drought thread traced from January 20th, 2017.

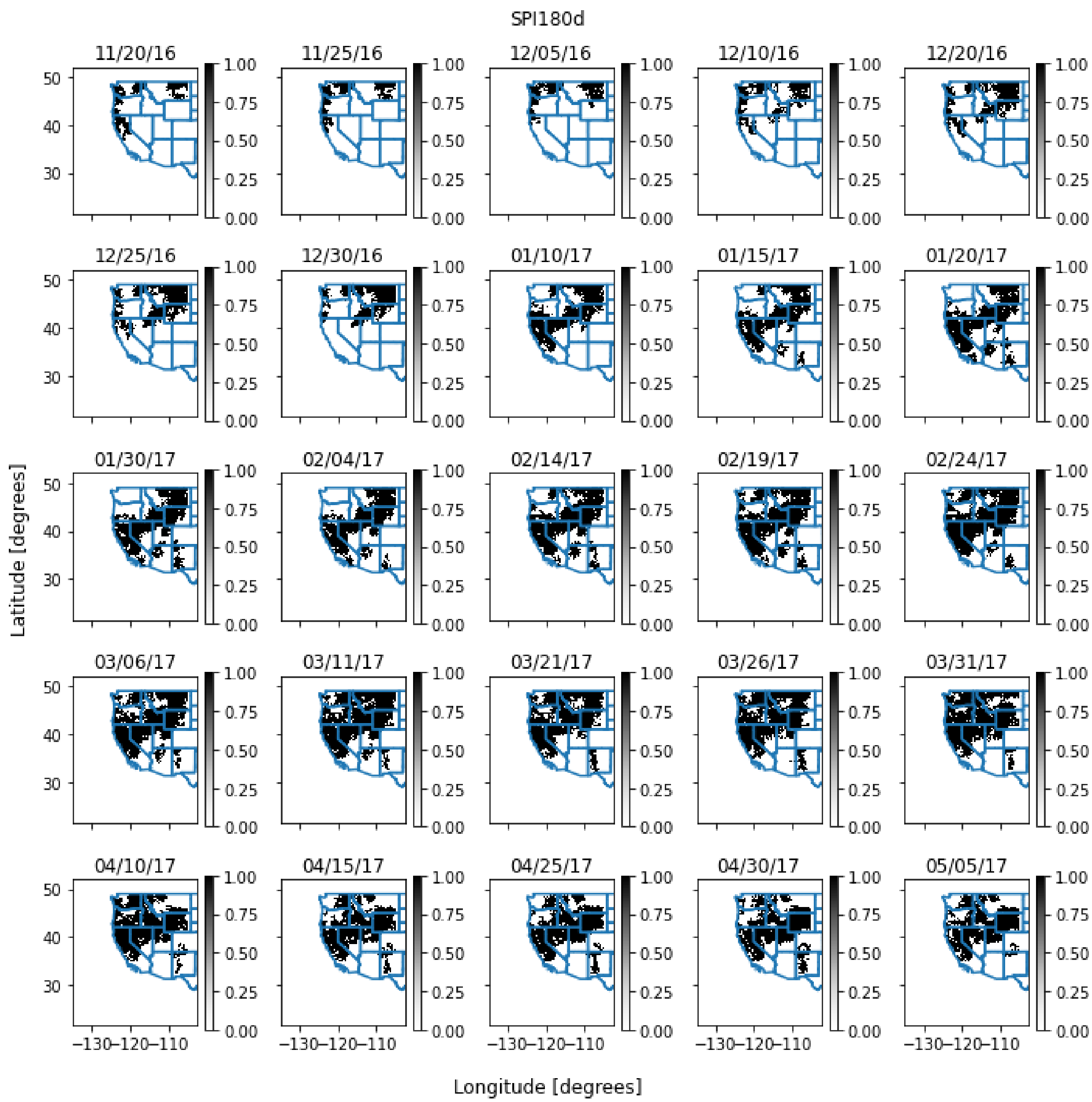


Figure 13c: Spatial plots for the SPI180d drought thread traced from January 20th, 2017.

Figure 13a-c: Drought threads from Figures 14a-c plotted on the western CONUS for visualization. Black signifies a drought of intensity D1 or greater, while white is no-drought. In blue, state lines are plotted for reference.

In the USDM, the drought thread begins in California, stretching north and westward for a month before starting to retract to the Southwest and shrink along the California coast.

Meanwhile the thread for SPI30d begins along the Montanna/Wyoming border before spreading southwesterly. SPI30d dominates the west except for Washington and Wyoming on January 20th, 2017, then retracts out of Arizona and begins to split into two drought areas on either side of Nevada. The drought areas reconverge across Idaho as the SPI30d thread spreads into Washington and retracts to the northwest. From there the drought thread splits into a focus in Wyoming and clustering in Washington/Oregon/Idaho. Both drought areas spread southwest before joining in northern Nevada. Lastly they split further in the northwest as patches of no-drought occur amongst the areas in drought.

The SPI180d thread begins scattered along the northern border and western coast, merging in Washington and increasing in area in eastern Montanna. The easterly drought area spreads southwest through Idaho before increasing in area in California. It primarily retains this shape from January to February before spreading into Washington and Oregon. By April 10th, 2017, it retracts from Montanna yet remains spread along its southwestern axis. Lastly it begins to retract from Washington and Oregon.

Next we see how these drought areas intersect with one another through AA and DA plotted during the times the drought networks overlap. Note how minimal agreement between USDM and SPI relative to their own areas matches the spatial plots encompassing different space throughout their evolution.

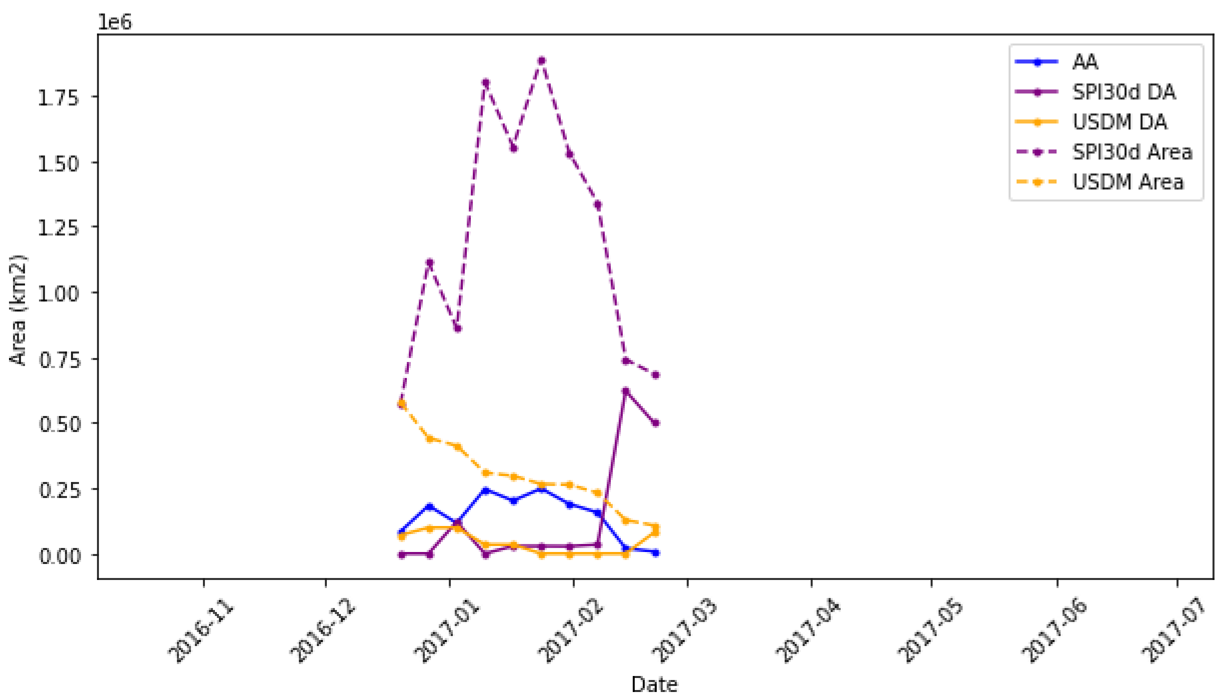


Figure 14a: AA, DA, and total areas for corresponding drought threads for USDM and SPI30d.

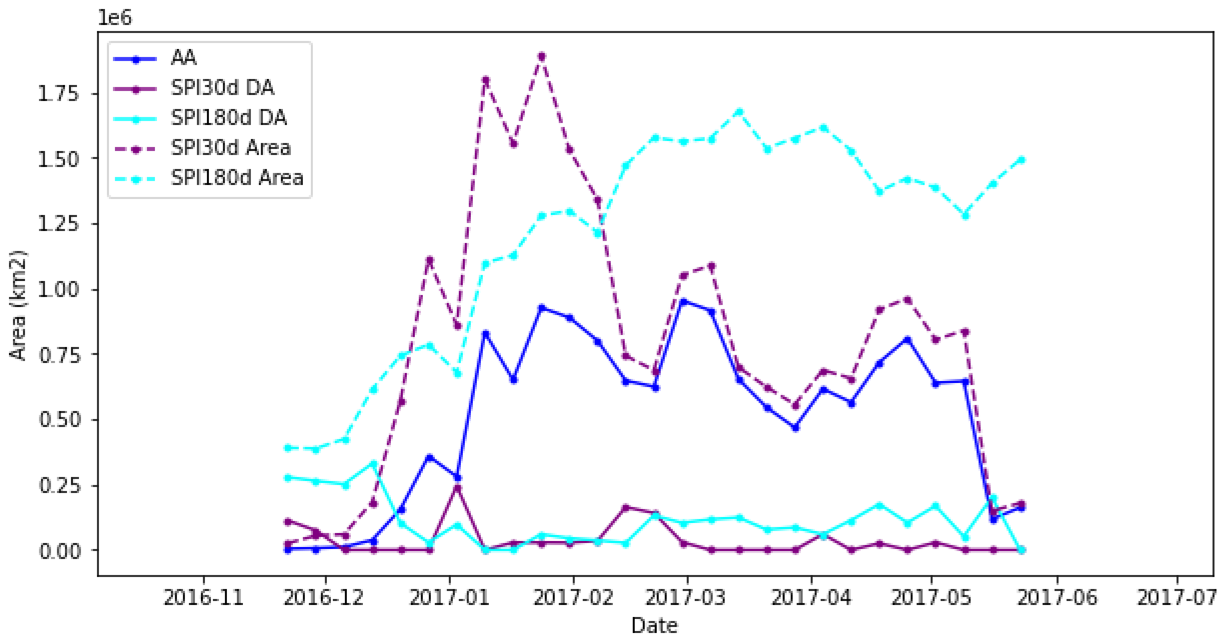


Figure 14b: AA, DA, and total areas for corresponding drought threads for SPI30d and SPI180d.

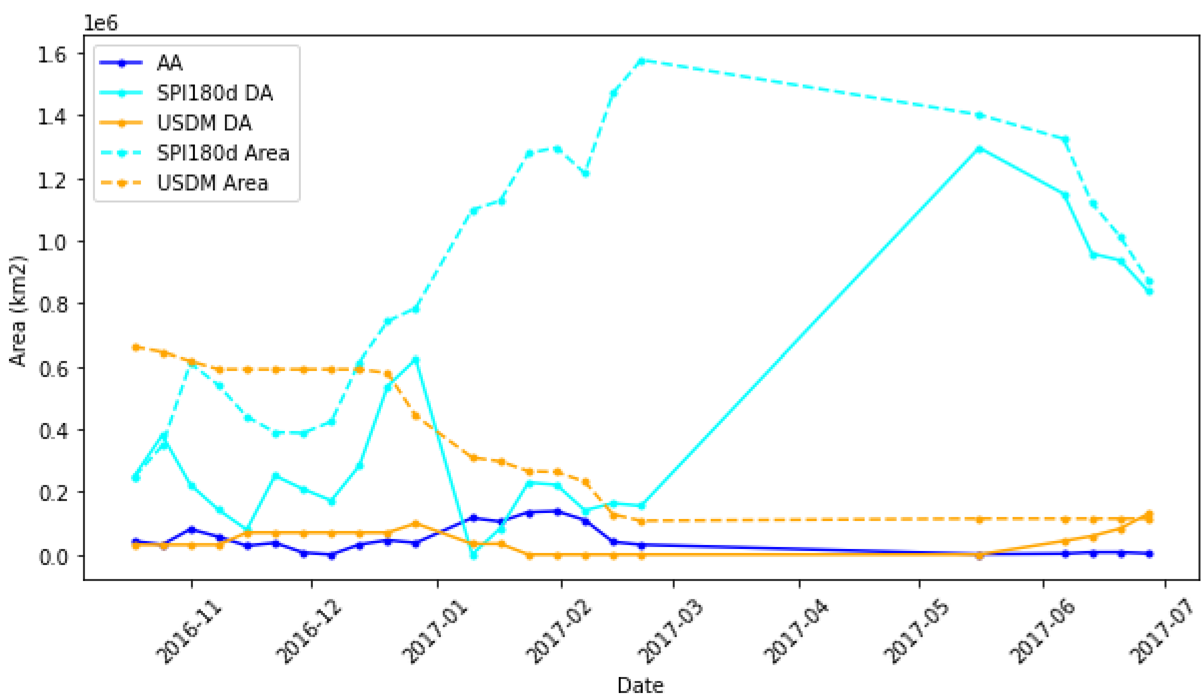


Figure 14c: AA, DA, and total areas for corresponding drought threads for SPI180d and USDM.

Figure 14a-c: Direct comparison by thread from intersection with SPI30d January 20th, 2017, for pairings of SPI30d, SPI180d, and USDM. Alignment Area (AA) and Disagreement Area (DA) are plotted as between the two metrics plotted in each subfigure, (12a is between SPI30d and

USDM, 12b is between SPI30d and SPI180d, and 12c is between SPI180d and USDM). Each plot also contains the total area of the thread at each time step for reference. Only times during which an overlap between two metric's drought areas exists are plotted, hence the interpolation in Figure 14c from late winter to mid spring 2017. This time period was selected as it contained the largest SPI30d area, lending to clear analysis.

In comparison to the USDM, SPI30d and SPI180d largely dominate in drought area during their plotted threads in Figures 14a and 14c, with the exception of USDM exceeding SPI180d until mid December 2016. SPI30d drought thread exceeds the drought area of SPI180d from late December 2016 to early February 2017 in Figure 14b.

From December 2016 to February 2017, SPI30d drought thread captures the majority of USDM drought thread as indicated by AA being near the total area of USDM drought area while USDM DA remains near zero. There is however some relatively small area that is not captured when USDM DA is non-zero. Until early February 2017, SPI30d drought thread is fairly contiguous with the USDM drought thread with its near-zero SPI30d DA. The rise in SPI30d DA during February 2017 to encompass most of the SPI30d drought area indicates that the USDM drought area is no longer contiguous with the SPI30d drought area.

In comparing SPI30d and SPI180d drought threads, December 2016 to February 2017 SPI30d drought thread is partly captured by SPI180d drought thread but does not match all of the thread, shown by AA being less than half that of SPI30d total area. From February to June 2017 AA largely follows the shape of SPI30d drought thread and is near in magnitude, meaning nearly all of SPI30d drought thread that is contiguous with SPI180d drought thread is overlapped. During the period of Figure 14b, DA remains low for both SPI30d and SPI180d, meaning that little area is not contiguous between the two drought threads.

Figure 14c depicts low AA between SPI180d and USDM from November 2016 to July 2017. From March to mid May 2017 there is no overlap between SPI180d drought thread and USDM drought thread, there are no contiguous drought blobs. Following May 2017 when there is overlap again, SPI180d and USDM barely have any common area, shown by high SPI180d DA and near zero AA.

3.2.2 Thread from July 14th, 2015

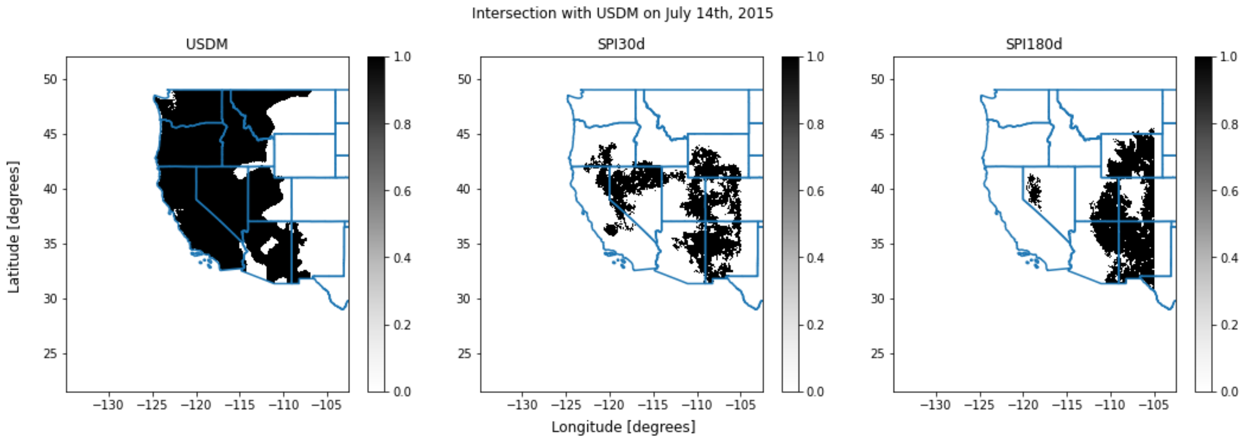


Figure 15: Intersection with USDM on July 14th, 2015, with SPI30d and SPI180d.

This example showcases an intersection between USDM, SPI30d, and SPI180d on July 14th, 2015, across the threads that they intersect with (Figure 15). Note the persistence of the USDM and how, while there is a notable snow drought in Washington during this time, drought is not exclusive to Washington.

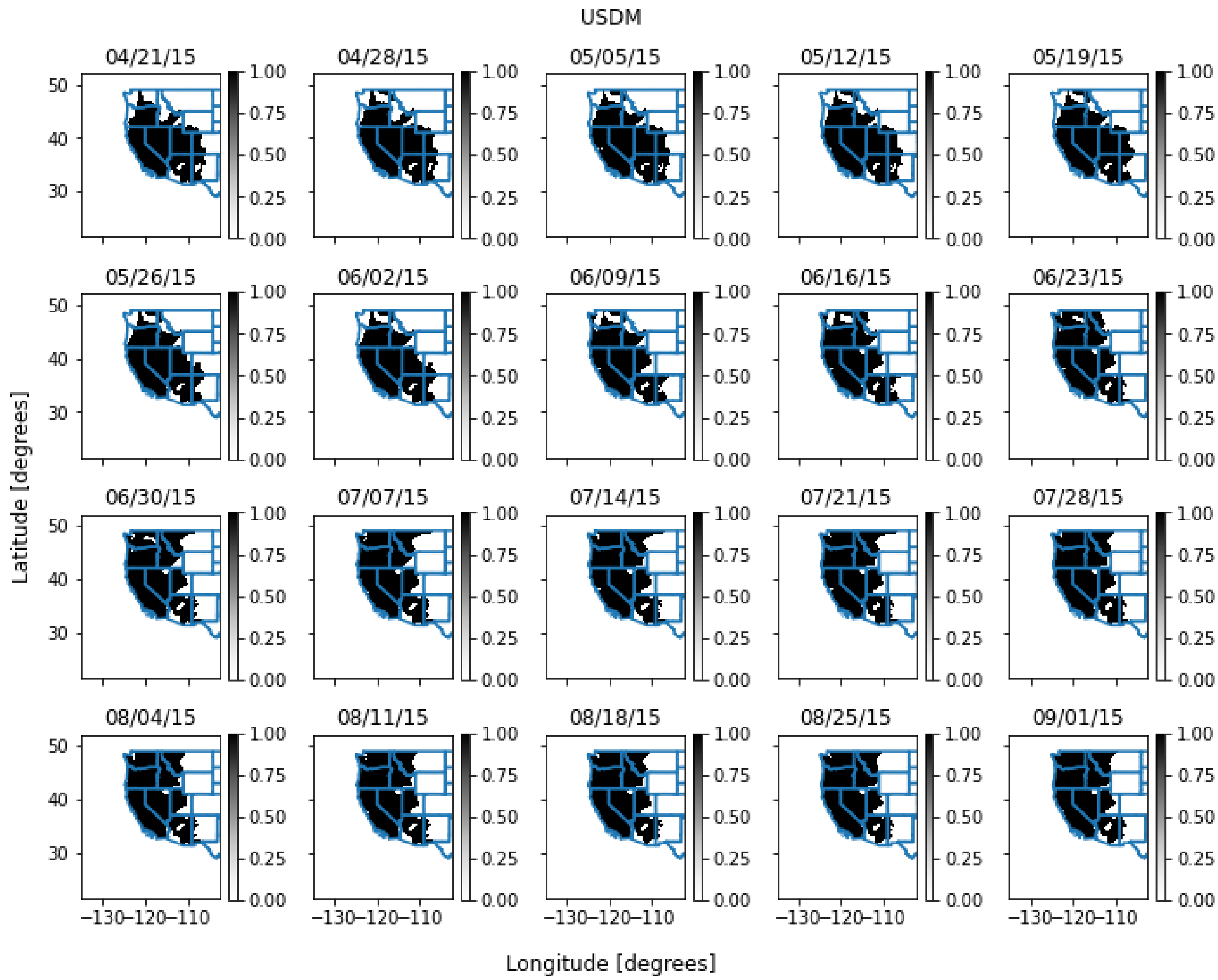


Figure 16a: Spatial plots for USDM drought thread traced from July 14th, 2015.

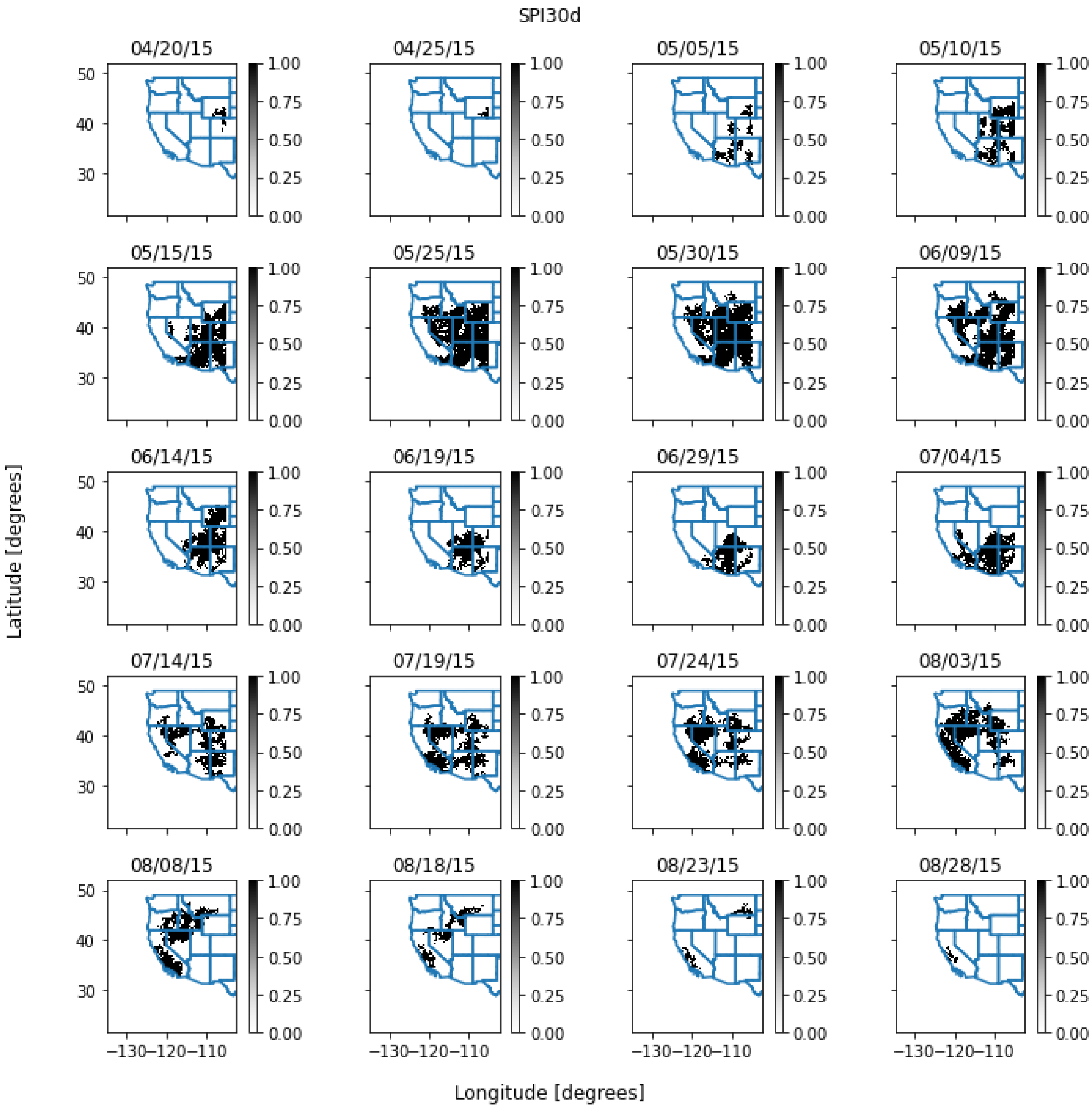


Figure 16b: Spatial plots for SPI30d drought thread traced from July 14th, 2015.

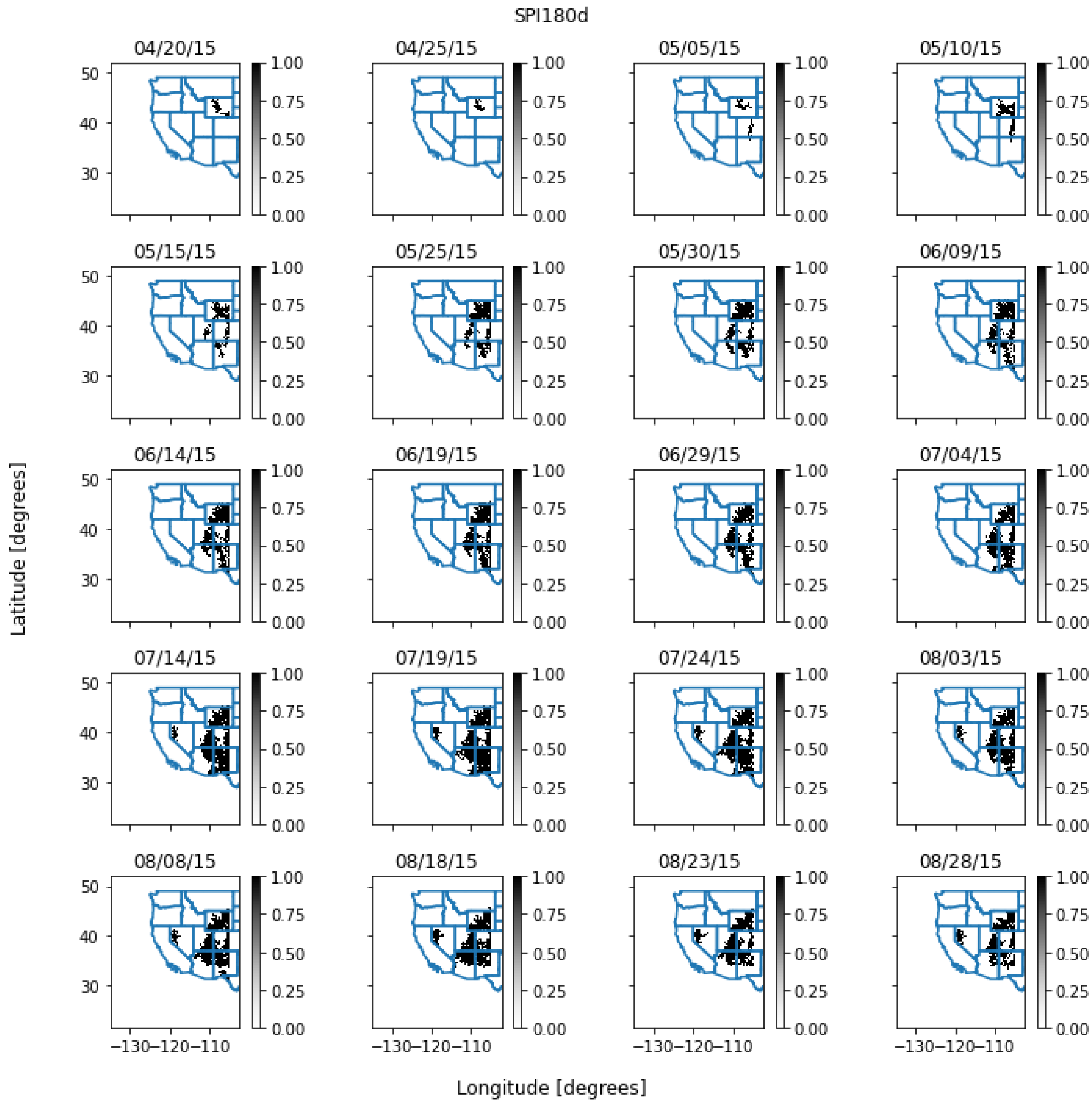


Figure 16c: Spatial plots for SPI180d drought thread traced from July 14th, 2015.

Figure 16a-c: Drought threads from figures 17a-c plotted on the western CONUS for visualization. Black signifies a drought of intensity D1 or greater, while white is no-drought. In blue, state lines are plotted for reference.

USDM is spread from Washington to western New Mexico and all of California. It largely does not change in shape for several months before fully expanding into Washington and beginning to retract along the drought area's eastern border.

SPI30d begins in southeastern Wyoming, spreading southward through Colorado and expanding into Arizona and New Mexico. It then expands westward through Utah and into

Nevada, slightly entering California along its eastern border but not expanding through it. On June 9th, 2015, SPI30d began to split from its western expansion that died out quickly. The remaining area stretching from Wyoming to Arizona/New Mexico retreats from Wyoming and consolidated around Arizona. It then forms a cluster in northwestern Nevada that spreads eastward and southward, yet retains a gap around southern Nevada. August 3rd, 2015, the gap around southern Nevada remains while Arizona recovers but part of New Mexico remains in drought. The drought area then retreats to the northwest before splitting to a portion being in western California and a portion along the Wyoming/Montana border.

SPI180d begins in Wyoming and remains relatively small through April before beginning to expand southwards in May. Wyoming becomes nearly completely covered by drought while parts of Utah, Colorado, New Mexico, and a sliver of Arizona become in drought. By July 14, 2015, roughly half of New Mexico and Arizona are in drought as specs of drought emerge in Nevada. Throughout this time a small amount of California has remained in drought without much change along the southern coast. Drought eventually begins to retreat from Arizona/New Mexico as parts of the drought blob are recovered.

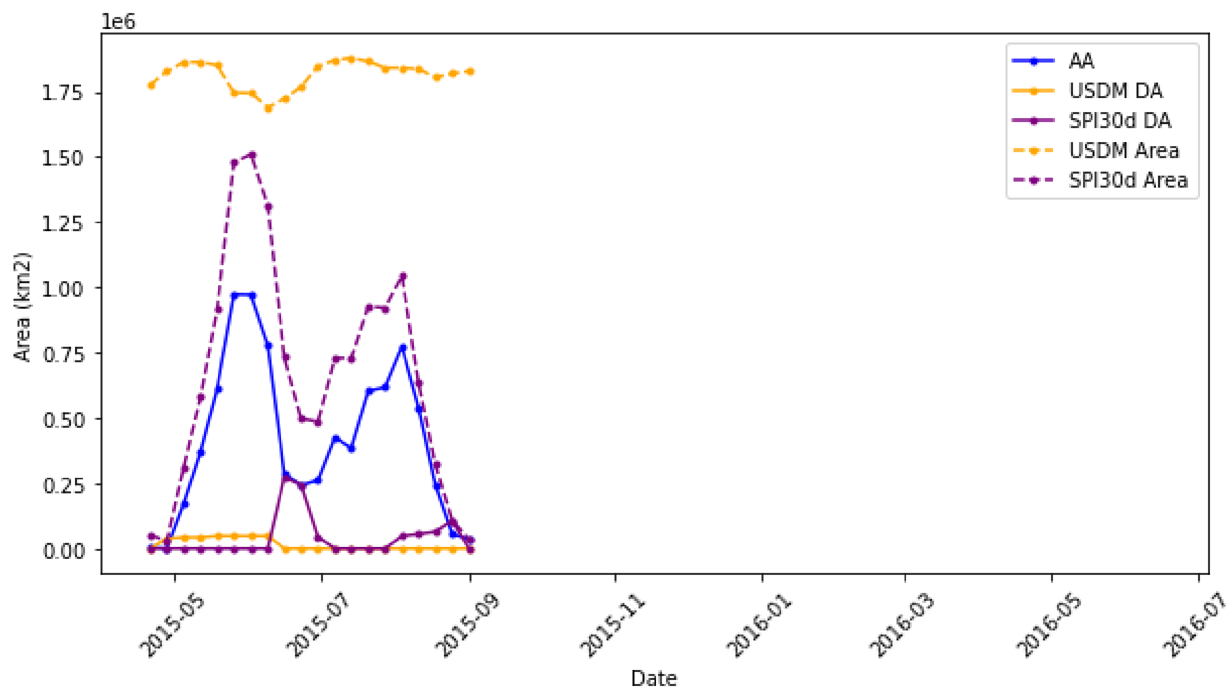


Figure 17a: AA, DA, and total area for corresponding drought threads for USDM and SPI30d.

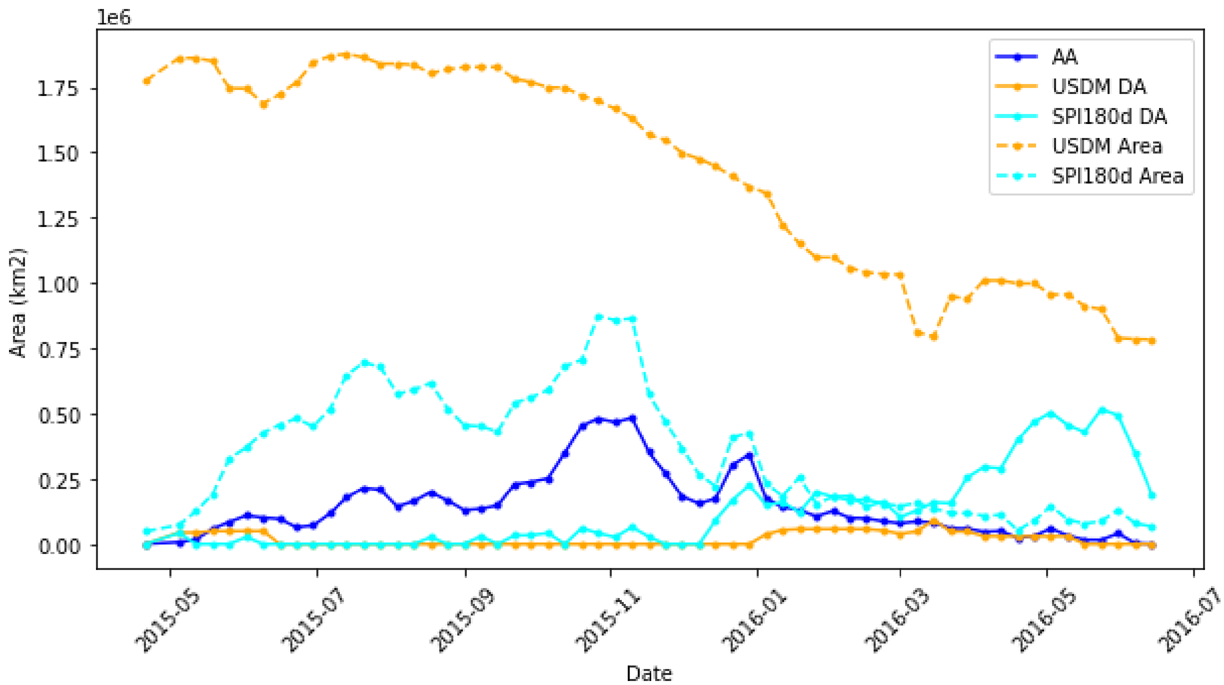


Figure 17b: AA, DA, and total area for corresponding drought threads for USDM and SPI180d.

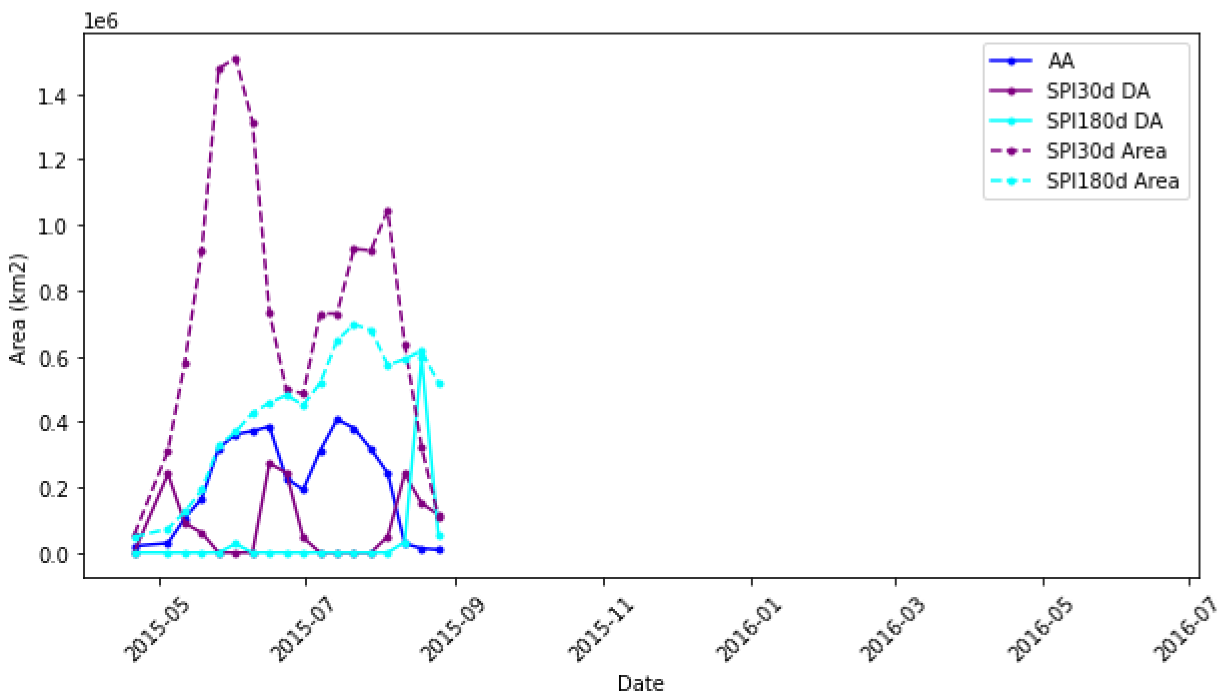


Figure 17c: AA, DA, and total area for corresponding drought threads for SPI30d and SPI180d.

Figure 17a-c: Direct comparison by thread from intersection with SPI30d July 14th, 2015, for pairings of SPI30d, SPI180d, and USDM. Alignment Area (AA) and Disagreement Area (DA) is *plotted as between the two metrics plotted in each subfigure, (14a is between SPI30d and USDM, 14b is between SPI30d and SPI180d, and 14c is between SPI180d and USDM). Each plot also contains the total area of the thread at each time step for reference.*

April to September 2015 SPI30d drought thread is mainly contiguous with USDM drought thread, shown by near zero DA and AA being near the total SPI30d drought area in Figure 17a. The exception to this is June 2015 when DA rises, indicating a region of SPI30d drought thread not being covered by the USDM drought thread. The USDM drought thread exceeds the SPI30d drought thread in area for this entire time, with near zero DA. AA largely follows the shape of the SPI30d drought area.

Figure 17b depicts direct comparison between the USDM drought thread and SPI180d drought thread from May 2015 to July 2016. While declining, the USDM drought thread largely exceeds the SPI180d drought thread in area for the entire time period. Around January 2016, SPI180d DA began to match then overtake AA in February.

Lastly, Figure 17c illustrates the relationship between SPI30d and SPI180d from mid-April to August 2015. SPI180d DA remains near zero from April through July, spiking to the full SPI180d dought thread area in August before coming back down before the end of the month. Meanwhile, SPI30d DA is non-zero for the majority of the time period, aside from being near-zero for the first and last drought blobs. AA closely matched SPI180d drought thread through May, indicating that nearly all of SPI180d drought thread is contained within SPI30d drought thread. SPI30d drought thread area is much larger than SPI180d drought thread area for May however, meaning that the SPI180d drought thread contained within it does not equally capture SPI30d drought thread. AA largely follows the shape of SPI180d drought thread through July.

Both of these examples demonstrate how despite having droughts that coincide with each other, USDM and SPI largely capture different types of droughts. SPI30d and SPI180d capture similar types of droughts but still have their differences due to their time windows. This means that even though USDM incorporates SPI in its decision making process, it still evolves differently from SPI. Similarly, even though SPI characterizes meteorological drought that influences many other types of drought, it evolves differently from USDM and based on the time window used.

3.3 Limitations and Considerations

3.3.1 Persistence

One problem encountered in performing CDA analysis is the matter of deciding when droughts should start and stop. Changing what constitutes the onset and termination of a drought impacts each metric presented in this paper. Imposing a minimum area of drought solved the problem of having droughts persist endlessly due to a few cells hanging on between events. Yet for metrics like the USDM, drought area is still larger than the minimum threshold when it shrinks between large events. Increasing the lower bounds of what area is large enough provides problems for metrics like SPI that have smaller drought areas in general that would be thrown out completely by too high of a filter.

This problem of persistence is exemplified in the USDM that can be traced as having a total of three distinct starting and stopping periods during the entire 20 year record here. When trying to provide some case studies by tracing a thread backwards and forwards, this persistence yielded in long threads, including one up to 11 years long. Yet when we talk about drought, such as the 2015 snow drought in Washington, we do not think of it as something that had been coming for a long time and persisted elsewhere further. This is where instituting physical boundaries shape the size and length of drought threads.

When this study began, we originally focused solely on Washington state. This made defining the infamous 2015 snow drought fairly straightforward. Yet we were uncertain to what degree the bounds of Washington were influencing our results as many origin/termination points laid upon the boundary of Washington state. To provide more room for our drought threads to play out, we expanded to everything west of longitude 105 on CONUS. This provided more tracks starting and ending not just on the geographic boundaries, but defining the specific 2015 drought became more murky. The 2015 snow drought appeared to move in the USDM across the map beyond Washington, making pinning down its definitive start and end much more complicated. The problem of persistence beyond boundaries still potentially exists in our region of study.

3.3.2 Thresholding

Another question present in CDA is what is an appropriate threshold with which to exclude drought areas? There can be a lot of noise present in metrics such as SPI due to them being products of meteorological data that can be highly heterogeneous in distribution. When converting SPI into synonymous USDM drought categories, a cut-off is imposed on what minimum value counts as drought and not. Yet there is a spectrum on which drought can occur, evident in the presentation of multiple categories in the USDM and SPI being on a continuum.

The matter of thresholding extends into what area is considered large enough to be a drought. In this paper we used a threshold of 25,000 km^2, but what about all the areas less than that? What are the impacts of small areas in drought? Our reasoning for excluding these areas was that they resulted in over-connecting drought events, resulting in abnormally long lifetimes from a handful of pixels persisting and being shared between drought events. Factoring in that coarse resolution relative to a small area may generalize the drought conditions within that region and may not be a reliable descriptor of that region.

Imposing multiple thresholds for defining drought areas, as done in section 3.1 by thresholding by D1 and D2, can only go so far into extreme categories. When attempting to threshold by D3 and D4, there was not enough data present in SPI30d and SPI180d. This is the problem with handling rare, extreme events, there may not be enough data due to their rarity. But the extreme events are some that we care most about because they will impose the most drastic impacts.

3.3.3 Comparing

The fundamental problem with comparing different metrics to each other is that USDM and SPI characterize different types of drought, USDM being a general metric and SPI being a meteorological metric. Even though the USDM incorporates data from SPI, it characterizes droughts on a fundamentally different timescale. Even SPI30d and SPI180d are intrinsically different by considering different windows, even if they are both descriptors of meteorological drought. An initial attempt to compare drought characterizations was a paired pixel correlation with lag between two measures. Pixels located at the same space in two metrics had their R correlation coefficient computed with lag up to +/- 20 time steps. Initially, lagging was thought to be able to improve the correlation between SPI and USDM drought characterizations since meteorological drought can precede other forms of drought as lack in precipitation translates to a lack of streamflow, snow, and groundwater. Lagging however did not improve the correlation between USDM and SPI30d or SPI180d, it remained highest when there was no lag.

An extension of this problem is the difficulty in identifying the same thread to compare drought networks to each other. Just because two networks overlap spatially at the same time, does not mean that they will evolve the same way or have the same origin. Not being able to identify the same thread easily presents challenges then in comparing, since it makes it murky whether differences are due to them being different threads or different metrics. Unfortunately, we cannot force one metric to process the same drought, only to experience the same conditions. Each metric has its own definition of what is drought, and therefore will only have certain types of droughts to compare against.

4 Conclusions

In this paper we present a methodology for comparing multiple drought metrics to each other using contiguous drought area analysis. For each drought metric we construct a drought network, a directed graph composed of drought blobs we call drought events. We develop an indirect and a direct means of comparing drought metrics. Indirectly we characterize the droughts of each metric by their lifetime, total distance traveled, displacement, average thread velocity, and similarity. Directly comparing drought networks for two metrics involved alignment and disagreement area, computing how much area is common and unique between two networks.

We found that USDM drought characterization is much more persistent and slow to change in comparison to SPI30d and SPI180d drought characterization. SPI30d drought characterization has rapid onset and recovery with many simultaneously occurring, fragmented drought areas. It moves the fastest and furthest of the three drought metric characterizations. SPI180d drought characterization has some of the fragmentation of SPI30d drought characterization but lives for longer while moving faster than USDM drought characterization but slower than SPI30d drought characterization.

The persistence of the USDM drought areas posed a problem for distinguishing between different drought threads. Meanwhile SPI30d and SPI180d drought areas having small fragmented areas required the imposition of a minimum area to classify drought events.

This paper pushes the field forward by presenting a means of extracting drought threads from a larger network of drought area and being able to compare those threads across different metrics. While the question of whether different drought metrics are intrinsically comparable remains, being able to compare metrics allows for dialogue across different types of drought and decision planning that may result from those characterizations.

Combining the indirect and the direct characterizations quantitatively provides a key realization: how drought is captured is highly dependent on how a metric defines drought. Being able to quantitatively describe differences in drought metrics provides a framework to actively compare droughts spatiotemporally, agnostic of the type of metric. To the best of our knowledge, this type of comparison has not been performed before despite advancements in characterizing drought through Contiguous Drought Area analysis.

As scientists and engineers, we define the metrics that describe deficits in water products, which entails immense power when we advocate for drought resiliency measures in a changing climate. Even selecting which SPI product will provide different descriptions of where drought lies. The tools provided in this paper advocate for the use of a multiplicity of metrics to nuance decisions made around drought monitoring.

While we aim for objectivity as scientists, we are still biased by what we pursue and our interest for pursuing it. Advocacy for drought resilience is one of these spheres where our bias can show up. Depending on what flavor of drought we are looking to analyze, we can shape our analysis to argue that a given product is what we should be looking at based on funding sources or areas of expertise. Bias does not implicate a failure as scientists, but a need for a means to step outside our areas of comfort and expertise. The scientific method enables our work to stand upon solid ground as we push forward new methods and findings, but ultimately does not address what we do with said findings.

The methods of this paper come in as a means to reconcile with there being many different products for characterizing drought. Each product has its own uses, USDM aiming to be a summary descriptor of drought and SPI being a measure of meteorological drought. Comparing them for the sake of performance is nonsensical as they each measure different things. Yet we still needed a means of communicating how each drought product varies for the sake of communicating to decision makers.

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