Synoptic-Scale Atmospheric Conditions Associated with Flash Drought Initiation in Puerto Rico and the Caribbean

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ABSTRACT

While conventional drought has been studied for many years, new research focuses on different aspects and types of drought. Flash Drought is a relatively new area of research in drought literature, dating back to the last ten to twenty years in the United States. Flash drought in the Caribbean has received minimal attention from researchers, but it has been studied in the United States primarily because of the 2012 flash drought event over the Great Plains. This study focuses on flash drought events in Puerto Rico and the Caribbean. Because the rapid onset and intensity of flash drought can potentially cause more devastation without established prediction methods, this research seeks to understand the synoptic scale atmospheric drivers of flash drought events. Recent occurrences of a flash drought event in this region include the 2015 event in Puerto Rico, which resulted in water rationing and shortages for residents of the island (Mote et al., 2017). The primary goal of this study is to understand how flash drought initiates and propagates for Puerto Rico and the Caribbean using two definitions of flash drought. One definition is based on soil moisture deficit, and the second definition is based on the Evaporative Demand Drought Index (EDDI), an experimental drought monitoring tool. Results suggest that an anomalous convection and positive moisture event followed by negative moisture anomalies and persistent subsidence contribute to flash drought event initiation and propagation. Additionally, large scale flash drought events seem to be initiating more frequently, suggesting that the island is becoming more susceptible to the devastations of flash drought.

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GENERAL AUDIENCE ABSTRACT

Drought in the United States is a well-known occurrence typically caused by high temperatures and low precipitation rates. States in the Western US like California, Arizona, Nevada, and more have been negatively impacted by persistent drought. These negative impacts include water rationing laws, struggling agricultural yield, and many days without precipitation. In recent years, it has been discovered that drought has a counterpart known as flash drought. Flash drought is to flash flooding as drought is to a floodplain. Floodplains are areas prone to persistent flooding, but flash flooding occurs in a matter of minutes or hours due to extremely intense precipitation and a lack of drainage for the water to leave. Flash drought is very similar to flash flooding due to the rapid onset and intensification. Flash drought has been studied for the United States in some cases, but there is very little known about flash drought in Puerto Rico and the Caribbean. This study seeks to understand how flash drought initiates and intensifies in Puerto Rico. Results of this study suggest that flash drought can initiate immediately after a large precipitation event that is followed by days without precipitation. Because of the amount of moisture after the precipitation, the atmosphere wants to evaporate that moisture back out. As more moisture is evaporated, the land becomes drier and drier, especially when there is no follow up precipitation. The lack of follow up precipitation is also explained in this study. It was found that following the big precipitation event, the atmosphere does not create more precipitation because of a persistent state of downward vertical motion. Upward vertical motion is needed for precipitation to occur, so the combination of downward vertical motion and dry air results in a flash drought event in Puerto Rico.

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Chapter 1: Introduction

Drought can have devastating impacts on water supply, agricultural productivity, and public health in any part of the world. While seasonal drought has been studied for many years, new research focuses on different aspects and types of drought. Flash Drought is a relatively new area of research in drought scientific literature, dating back to the last ten to twenty years in the United States. While flash drought's definition in applied research is not uniform, the conceptual definition is described as an occurrence of drought with high intensity over a short time, typically over four to eight weeks. Flash drought in the Caribbean has received minimal attention from researchers compared to conventional drought, but it has been studied in the United States primarily due to the 2012 major flash drought event over the Great Plains. This event cost over $17 billion in Federal crop indemnity payments, with the inflation-adjusted cost reaching over $30 billion for the entire US (Chen et al., 2019; Otkin et al., 2016).

Conventional drought differs from flash drought primarily due to its temporal scale being over multiple months with a more gradual onset, intensity, and impact. While conventional drought's impact can still be very damaging, mitigation and adaptation strategies for this type of drought are well understood and can be implemented more easily than for flash drought because of the temporal scale. Common impacts of conventional drought include reduced crop productivity, increased fire hazard, and increased livestock and wildlife mortality rates (Wilhite et al., 2007). Some strategies exist to predict conventional drought in preparation for these hazards, but the rapid onset and intensity of flash drought is currently far less predictable.

This scientific research will address the research needs related to flash drought events. Prediction of these events is essential to mitigation efforts; therefore, this research seeks to understand the synoptic scale atmospheric drivers of flash drought events to help improve predictability. The rapid onset and intensity of flash drought can potentially cause more devastation than conventional drought because there is currently no consensus on how to predict flash drought events. Because research efforts have been largely focused on the Continental United States (CONUS), flash drought events in Puerto Rico and the Caribbean are greatly understudied in the current literature. Recent occurrences of a flash drought event in this region include the 2015 event in Puerto Rico, which resulted in water rationing and shortages for residents of the island (Mote et al., 2017). These groundwater-limited islands are uniquely vulnerable societally, ecologically, and agriculturally by flash drought events due to their geographic characteristics. Therefore, this research seeks to better understand the cause of hydrological impacts of flash drought events on these islands. Considering the basic and applied research needs presented, I will examine the following research questions:

1. What are the modes of variability in the synoptic scale atmospheric drivers influencing flash drought events in Puerto Rico?
2. Can self-organizing maps help determine which synoptic modes of variability are most conducive to severe, long-duration flash drought events?

These investigative questions are important for targeting the results of this initial research to guide future work in this field. Much of this study is at the forefront of flash drought research in this region of the world and understanding the modes of variability are an important step in uncovering potential causes of flash drought. Many studies have been conducted for flash drought in the Continental United States, and there is much to be learned and applied from the literature.

Chapter 2: Literature Review

2.1 Research Context

This research is situated within the field of hydrometeorology, which involves the terrestrial and atmospheric interactions with the hydrological cycle including floods, tropical cyclones, precipitation variability, and drought. The hydrological cycle is in constant flux due to continually changing atmospheric and landscape conditions, which ultimately impact humans differently every day. The hydrological cycle's sudden shifts can affect homes, businesses, and governments' financial stability and access to water. The ramifications for drought, specifically flash drought, mostly impact people's access to water, which can affect financial stability, especially in the agricultural sector. Some studies (Jin et al., 2019; Otkin et al., 2016) specifically analyze the impacts of flash drought events, while others assess the frequency and variability of flash drought overall (Ford & Labosier, 2017; Koster et al., 2019). One of the most impactful flash drought events in the United States in recent history occurred in 2012 over the Great Plains. While some research identified the key characteristics that triggered this event, others recognized the financial and crop losses due to this region's significant agricultural production (Jin et al., 2019; Otkin et al., 2016). Because of the losses associated with flash drought, research has focused on predicting these events to mitigate the damage that flash drought can cause. Flash drought characteristics, like the onset, intensity, and frequency, have been linked to changes in evapotranspiration, soil moisture, and precipitation (Chen et al., 2019). Further understanding of these flash drought characteristics and the synoptic scale atmospheric drivers causing these changes requires knowledge of the hydrological cycle, atmospheric and terrestrial interactions, and the variability associated with these interactions. Defining flash drought, especially in a novel study region like the Caribbean and Puerto Rico, is an important first step in conducting this research.

2.2 Flash Drought Definitions and Characteristics

A critical issue in flash drought research is reaching a consensus on a clear definition for this event. Flash drought is inherently difficult to define because the definition is dependent on the dataset and study area. If flash drought events were defined based only on how the United States Drought Monitor defines drought (Chen et al., 2019), then the definition would most likely not work in other areas of the world where flash drought events are also prevalent.

Because definitions of flash drought vary based on regional and temporal differences, it is important to identify common characteristics of these definitions. One key characteristic used to identify flash drought events is soil moisture percentile change. Reduced soil moisture anomalies are typically indicators of a drought, and in this context, a considerable reduction in a short period is associated with flash drought events. The specific definitions of “considerable reduction” and “short time period” vary some, but the trend typically is a soil moisture value that drops below the 20^{th} percentile value over a 20-30 day period (Christian et al., 2019; Ford et al., 2015; Ford & Labosier, 2017; Koster et al., 2019; Yuan et al., 2019). While this reduction in soil moisture is studied in different ways depending on the study area and type of research, the 20^{th} percentile is a key indicator of a flash drought when seeking a unifying definition. Further, while soil moisture is an important indicator of flash drought, other research seeks to define flash drought using different parameters.

Evapotranspiration (ET) anomalies are commonly used to help identify and predict flash drought events. ET signals vary in time and intensity in relation to flash drought events, but a positive ET anomaly typically is evidence of depleting soil moisture reserves (Otkin et al., 2018).

Because of this relationship with soil moisture levels, monitoring ET anomalies for rapid change, especially from positive to negative, can be a good indicator for flash drought onset (Chen et al., 2019). The Evaporative Stress Index (ESI) is one such tool that measures ET anomalies. A clear flash drought definition may not be necessary in cases of reanalysis of a flash drought event, but the ESI can be used to help understand how ET may have indicated this event, thus justifying changes in ET as a method of defining future flash drought events (Otkin et al., 2016). Although a clear definition may not be necessary in this review of a flash drought event, it should be noted that a reduction in soil moisture below the 20th percentile and a positive ET anomaly are significant indicators that will be useful in future research.

When initially reading through the flash drought literature, many of the definitions were centered around soil moisture deficits, which is an intuitive and appropriate methodology. Another metric that has started to gain more ground in the literature is called the Evaporative Demand Drought Index (EDDI). The EDDI measures the evaporative dynamics of drought, assessing the response of evaporative demand (E_0) to surface drying anomalies (Hobbins et al., 2016). EDDI is based on E_0 and derived using the ASCE standardized reference ET equation:

$$E_0 = \frac{0.408\Delta}{\Delta + \gamma(1 + C_d U)}(R_n + L_n - G)\frac{86\,400}{10^6} + \frac{\gamma \frac{C_n}{T_{\text{air}}}}{\Delta + \gamma(1 + C_d U)} U \frac{e_{\text{sat}} - e_a}{10^3},$$

Figure 2.1: Evaporative Demand calculation based on the ASCE standardized reference ET equation (Hobbins et al., 2016).

Variable	Unit	Description
E_0	mm day^{-1}	Atmospheric evaporative demand
Δ	Pa K^{-1}	Slope of the saturated vapor pressure-temperature curve at the 2-m air temperature (K)
y	Pa K^{-1}	Psychrometric constant
U	m s^{-1}	Wind speed at 2-m height
R_n	W m^{-2}	Net incoming shortwave radiation
L_n	W m^{-2}	Net incoming longwave radiation
G	W m^{-2}	Downward ground heat flux
e_{sat}	Pa	Saturated vapor pressure
e_a	Pa	Actual vapor pressure

Table 2.1: Description of variables for equation in Figure 2.1.

EDDI uses a nonparametric approach, where empirically derived probabilities are obtained through an inverse normal approximation (Vicente-Serrano et al., 2010).

$$P(E_{0_i}) = \frac{i - 0.33}{n + 0.33},$$

Figure 2.2: $P(E_{0i})$ is the empirical probability of E_{0i}, which is aggregated across the period of interest.

$$\mathrm{EDDI} = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3}$$

Figure 2.3: Final EDDI equation. W is determined by the value of $P(E_0)$, and C and d values are constants (see Hobbins et al. 2016 for more details).

EDDI is an experimental drought monitoring tool that examines the anomalous evaporative demand for a given location (Physical Science Laboratory, 2022). It often is sensitive to drought before other common drought metrics (e.g. soil moisture, precipitation deficits; Hobbins et al. 2016). Its primary objective for development is to serve as an early warning tool for impending drought and flash drought. Because EDDI is sensitive to drought before other common drought metrics, EDDI can detect the potential initiation of drought before these metrics. A soil moisture deficit, for example, is a reactive response to drought. EDDI has the potential to detect drought before the soil moisture response, thus providing a potential better method of predicting flash drought events. While EDDI can be used to diagnose long-term drought and drought severity, the novelty of EDDI is its ability to detect abrupt, significant changes in evaporative demand. This sudden increase in evaporative demand may go unnoticed until the drought is already in place, so monitoring EDDI as a way to understand flash drought initiation could be important.

To calculate EDDI, the atmospheric variables shown in Table 2.1 need to be acquired for study locations. In this study, reanalysis data on a 9-km grid are leveraged. The next step is to calculate the reference ET and aggregate it over the time period (e.g. 5-day, 7-day, monthly). Lastly, the aggregated values are compared to the climatology. The EDDI is generated daily with a 5-day lag time, which is also referred to as a pentad. In the tropics, particularly in the study domain, drought evolves at short time-scales due to large atmospheric demand driven by intense solar heating.

An EDDI-based flash drought definition that indicates a rapid onset of drought is a 50% increase in percentile of EDDI (towards drying) over two weeks, which is sustained for two weeks afterward (Pendergrass et al., 2020). A slightly refined definition is employed in this study where the 50% increase must happen over a 15-day window (3 pentads) and be sustained for another 15-day window. This allows for better resolution of tropical drying, which has been shown to evolve over shorter time periods than observed in the mid-latitudes (e.g. Ramseyer and Mote 2018). This

EDDI definition provides a novel flash drought definition at the leading edge of the flash drought literature. By leveraging EDDI, this flash drought definition is not based on the USDM and has not been incorporated into drought research for Puerto Rico and the Caribbean.

2.3 Synoptic Scale Drivers in US

Once a flash drought event is defined, there are many aspects to be understood about the frequency, onset, intensification, prediction, and climatology of these events. Key characteristics of flash drought include precipitation, evapotranspiration, and soil moisture, but the causes of these variables involve changes in weather patterns. Understanding the synoptic scale drivers of these flash drought features will ultimately enhance the prediction and understanding of why flash drought events occur. Very few studies have been conducted on the meteorological conditions associated with flash drought for CONUS, and even fewer have focused on Puerto Rico and the Caribbean.

Ford & Labosier, 2017 studied the meteorological conditions of flash drought in the Eastern United States to better understand the onset of flash drought events. This study's data included hourly observations of temperature, dew point, pressure, relative humidity, precipitation, and wind speed from weather stations in the study area from 1979 to 2010 (Ford & Labosier, 2017). Soil moisture data was included from the NLDAS-2 model dataset. While these data are overall less accurate than in situ observations, the modeled data still provides a quality understanding of this region's soil moisture variability. In situ observations are rare and difficult to obtain, especially in regions like Puerto Rico and the Caribbean, so high-quality modeled data is often required for this type of research. Daily anomalies of the soil moisture and weather data were averaged to pentad-scale, a method used to decrease noise and capture the rapid onset of the flash drought events (Ford & Labosier, 2017). Before selecting the reanalysis atmospheric data, the study defined flash drought events as decreased soil moisture below the 20th percentile in 4 pentads or less. Synoptic-scale mid- and upper- level atmospheric data from the North American Regional Reanalysis datasets were utilized to determine the atmospheric conditions prior to flash drought events.

This study found that the surface meteorological conditions before a flash drought event included increased evaporative demand, decreased precipitation and humidity, and soil moisture deficit (Ford & Labosier, 2017). These conditions are related to ridging in the mid-to-upper-level troposphere, specifically located to the west-northwest of the study area. This ridging pattern was consistent at each lead time with each region except for the South, so this observation suggests that the persistence, rather than just the establishment, of a mid-level ridge is necessary for flash drought onset (Ford & Labosier, 2017). While this ridging pattern showed potential for predicting the onset of flash drought in the eastern United States, the same cannot be assumed for Puerto Rico and the Caribbean, emphasizing the importance of similar studies in this region.

2.4 Puerto Rico Precipitation Variability and Drought

There has been little research on flash drought in Puerto Rico and the Caribbean in general; however, some studies have identified potential indicators for rainfall variability and drought in this region. A better understanding of rainfall in Puerto Rico will help identify how negative precipitation or positive evapotranspiration anomalies occur, which are both important for flash drought development.

Because of Puerto Rico's unique geographic location, precipitation patterns are caused by different processes than the mid-latitudes. Precipitation in Puerto Rico involves multiple wet seasons separated by dry periods (Comarazamy & González, 2008; Daly et al., 2003). Topography, exposure and direction of predominant winds, and proximity to the ocean are important for the spatial precipitation over the island as well (Daly et al., 2003). Rather than steadily consistent rain throughout the year, much of the annual precipitation in Puerto Rico is due to intense showers from easterly waves and tropical disturbances from May to October (Larsen, 2000). Urban areas, like San Juan, for example, influence precipitation patterns but to a lesser extent than topography, which has shown to increase precipitation at a rate of approximately 140% per km of elevation (Comarazamy & González, 2008; Daly et al., 2003). Overall, the most precipitation on the island occurs in the Luquillo Mountains of northeast Puerto Rico, home to the El Yunque National Forest.

Using an artificial neural network (ANN), Ramseyer & Mote, 2016 analyzed which predictor variables were most statistically significant for rainfall in Puerto Rico. Overall, the most important atmospheric predictor variables are low tropospheric specific humidity and low tropospheric u-winds. Air at 1000 hPa is transported by easterly trade winds to the Luquillo Mountains, forcing ascent up the mountain range's windward side, which provides more lift and allows for condensation to occur. Coupled with high humidity, there is more instability and more moisture content in the air, causing precipitation. Also, the low-level specific humidity is related to SST levels and the low-level winds. Decreases in trade winds lead to increased SSTs, enhanced surface evaporation, and increased instability, allowing for more rainfall in the Caribbean. Lastly, increased trade winds, wind stress and turbulent mixing leads to cooler SSTs, less convection, and more atmospheric stability leading to less precipitation (Ramseyer & Mote, 2016), which has major implications for a potential flash drought event. Further understanding about what variables lead to decreased precipitation in Puerto Rico provides more information about the onset and intensification of flash drought.

As a follow-up to the aforementioned study, Ramseyer et al., 2019 introduced another ANN to predict the future variability of rainfall in the El Yunque National Forest, where the highest annual rainfall occurs on the island. Results suggest that more early rainfall season dry days will occur by mid-century, primarily driven by increases in 1000-700 hPa bulk wind shear and temperature throughout the troposphere. Also, while the ANN did not account for total precipitation, it can be inferred because early rainfall season total precipitation is highly correlated with the dry day frequency. The mean early rainfall season at mid-century will decrease by 26% (Ramseyer et al., 2019), so this model provides more understanding of precipitation processes in Puerto Rico and provides insight into how these processes will change in the future. With potentially even less rainfall occurring in the future, the need to study flash drought in this region becomes even more important.

Drought and flash drought often are associated with negative precipitation anomalies, so it is important to understand atmospheric drivers leading to decreased rainfall. Mote et al. 2017 analyzed the impact of the Saharan Air Layer (SAL) as a potential rainfall suppressant for the Eastern Caribbean. While there are competing schools of thought on impacts of El Nino/Southern Oscillation (ENSO) on precipitation in the Caribbean, the summer 2015 drought in eastern Puerto Rico was associated with the strong ENSO warm event occurring at that time (Mote et al., 2017). Another rainfall suppressant could be the Saharan Air Layer, a dry, dust-rich air mass transported from the Saharan Desert of Africa to the Caribbean in the mid to upper atmosphere. This air layer is most active in mid-June to late July, resulting in drier than usual conditions for the Caribbean. The SAL transports high concentrations of mineral dust from Africa, and these aerosols may inhibit convective cloud development and rainfall. These drier conditions contributed to a reduction in rainfall for the 2015 Puerto Rico drought by approximately 45%. While 2015 had a strong El Nino phase and a positive North Atlantic Oscillation (NAO), which have shown to contribute to reduced rainfall, the drought was much more closely associated with the presence of the SAL. Better tracking and understanding of the SAL could be important for understanding drought onset, intensity, and frequency in Puerto Rico (Mote et al., 2017).

Limited studies have been conducted pertaining to the impacts of the 2015 drought in Puerto Rico, where the island saw a very significant decrease in water resources for months. Droughts have historically been an issue for the island, with other significant events occurring in the mid-1960s, early and mid-1970's, and the mid-1990's (Mote et al., 2017). The 2015 drought affected much of the Caribbean basin, but the relatively dense population of Puerto Rico impacted the island socially and ecologically in a much more drastic way than in the past (Figure 2.4). With over 2 million people in the San Juan metropolitan area along with the El Yunque National Forest, which is the only rainforest in the U.S. National Forest system, Puerto Rico is highly vulnerable to such a high impact drought. Municipal water supplies deplete, leading to water rationing and shortages, but there are also impacts to the highly biodiverse rainforest, including the slow recovery of fine-root biomass, limited access to microhabitats, and long-term declines in amphibians (Beard et al., 2005; Burrowes et al., 2004; Covich et al., 2003).

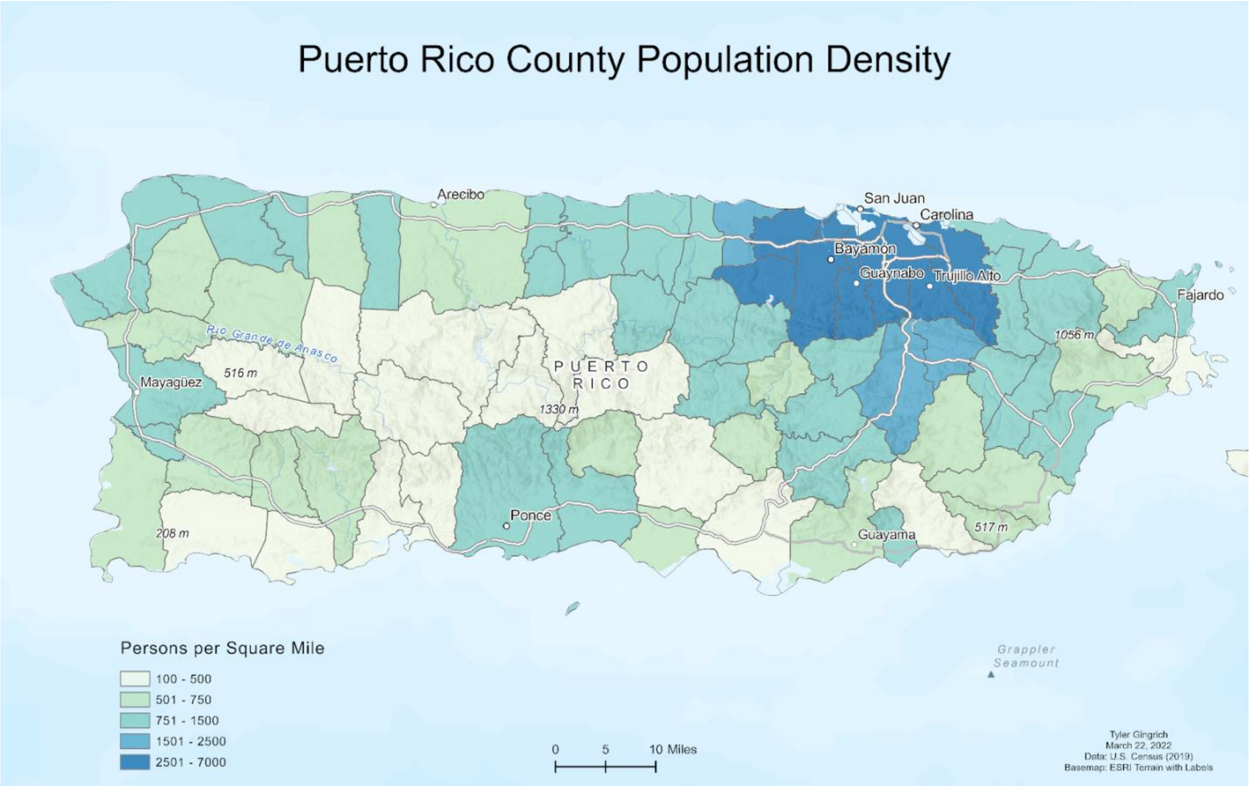


Figure 2.4: Population reference map for Puerto Rico.

2.5 SOM Applications in Atmospheric Sciences

Research in the atmospheric sciences often employs machine learning methodologies like artificial neural networks, self-organizing maps, and support vector machines to improve weather prediction and understand climatological patterns (Radhika & Shashi, 2009; Ramseyer & Mote, 2016; Sheridan & Lee, 2011). Artificial neural networks allow for non-linear functions to establish patterns between predictor variables and the desired output, like rainfall, at a location. These results of the ANN can be examined to determine the importance of each of the predictor variables on the results (Ramseyer & Mote, 2016). Self-organizing maps (SOMs), when used in this context, aim to identify and classify clusters of atmospheric conditions that lead to the variability at a certain location (Ramseyer & Mote, 2018; Sheridan & Lee, 2011). Lastly, support vector machines (SVM) map data into a feature space using a nonlinear mapping function to construct a hyperplane in new space (Radhika & Shashi, 2009). While each of these methods along with many of the other machine learning techniques have strengths and weaknesses, the most appropriate approach for this study will be self-organizing maps due to their ability to preserve all data inputs and their geovisualization capabilities.

SOMs have been employed in atmospheric science research since the beginning of the 21st century in numerous applications including assessing sea level pressure and precipitation in the Northeast US, understanding climate and sea surface temperature variability, temperature extremes in Alaska, water vapor transport to the Greenland Ice Sheet, and many more (Cassano et al., 2015; Hewitson & Crane, 2002; Mattingly et al., 2016; Morioka et al., 2010). A major strength of SOMs in atmospheric science applications is the capability to classify high dimensional data into low dimensional data (Morioka et al., 2010). SOMs are like a cluster analysis in this way. Given a multi-dimensional dataset, the SOM will place a number of nodes in the data space such that the distribution of nodes is representative of the nonlinear, multi-dimensional distribution function, where nodes are closely spaced or "clustered" in regions of high data density (Hewitson & Crane, 2002). SOMs differ from cluster algorithms in that they seek to find nodes or points in the data space that are representative of the nearby observations, thus helping to describe the multi-dimensional data rather than simply group the data (Hewitson & Crane, 2002). For the nodes to group accordingly, they are modified through a learning-rate parameter, which nudges the nodes as new input vectors are added to the SOM (Sheridan & Lee, 2011). The unique aspect of the SOM in this respect is that not only is the winning node, which is the node whose Euclidean distance is closest to the input vector, adjusted, but also the winning node's neighbor is adjusted through a distance array function (Hewitson & Crane, 2002; Sheridan & Lee, 2011). As input vectors are run through the SOM, the nodes modify more, thus ‘self-organizing’ into a pattern where similar nodes are closer and different nodes are farther apart (Sheridan & Lee, 2011).

There are numerous advantages to employing SOMs in atmospheric science research compared to downscaling and synoptic classification processes. The learning process of the SOM can parse out atmospheric phenomena extremely well. For example, when assessing sea level pressure, high pressure dominant patterns will be on one side of the SOM while low pressure dominant patterns will be on the other side, with transitions in a continuum in between (Sheridan & Lee, 2011). Similarly, this same pattern can be seen when analyzing ENSO phases (Leloup et al., 2006). The ability to parse data into the extremes allows for excellent visualization of atmospheric anomalies, with positive anomalies mapping to the first few nodes and negative anomalies mapping to the last few nodes or vice versa. Calculating and visualizing anomalies is a common and effective technique for understanding changes in atmospheric patterns. Additionally, the probability density is preserved, so more nodes are placed in data rich areas and outliers are less likely to be assigned to an unrepresentative data cluster (Nicholls et al., 2010; Sheridan & Lee, 2011). Another advantage of using SOMs is that data can be interpolated with a SOM; therefore, this methodology is appropriate for handling any missing values (Hewitson & Crane, 2002; Sheridan & Lee, 2011). Additionally, SOMs offer a great advantage in data visualization because the method allows for the utilization of multiple visualization techniques, thus allowing for a clearer depiction of the SOM data (Sheridan & Lee, 2011). Lastly, the purpose of implementing SOMs in this study is not to predict future flash drought events; conversely, the SOM methodology in this study is used to better understand how atmospheric patterns are associated with and potentially lead to flash drought events.

2.6 Summary

Flash drought events are extremely important to understand, especially in terms of prediction of onset, intensity, and frequency. These events can induce significant losses to agriculture, municipal water supply, and more. Research about flash drought has become popular in the last decade, but there is still much more work to be done, particularly in study areas outside of CONUS. An improved understanding of the synoptic-scale atmospheric drivers of flash drought will improve forecasts and reduce the impacts of such events. Flash drought definitions vary based on different datasets and parameters, but overall, flash drought's danger lies in its rapid onset and intensification without appropriate prediction methods in place. Factors such as soil moisture, evapotranspiration/humidity, and precipitation are studied in a variety of ways to better understand and predict flash drought. While this type of research has been conducted in the United States and some other parts of the world, little research has assessed Puerto Rico and the Caribbean region. Understanding flash drought in this region is important because while rainfall in the tropics is common, any change in the duration or intensity of the dry periods can be devastating on the municipal water supply. It is imperative to better understand and predict flash drought in this region because of its human impact and vulnerability. Municipalities must have the time and resources to adapt to these sudden changes. This research will seek to understand the atmospheric drivers causing flash drought events in the Caribbean using machine learning techniques such as self-organizing maps. The stress that the 2015 Puerto Rico drought event caused on the municipal water supply is one significant example, but other past and present examples will be analyzed as well.

Chapter 3: Methodology

3.1 Overview of Data and Methods

In this study, the synoptic forcing mechanisms for flash drought initiation and propagation are explored by:

1. Calculating flash drought using two separate, unique definitions:
    A. The first definition incorporates a soil moisture deficit based on the Ford & Labosier, 2017 methodology. This definition calculates flash drought by the days where soil moisture starts over the 40th percentile to drops below the 20th percentile in less than 20 days using GLDAS data available from 2000-2020.
    B. A second flash drought definition is used to provide consilience with the soil moisture-based definition. Flash drought is defined using the ERA5-Land derived evaporative drought demand index (EDDI). Using this definition, EDDI must increase in percentile by 50% within 3 pentads (e.g. 15 days) and then be sustained for another 3 pentads (Pendergrass et al. 2020).
2. Analyzing the synoptic atmospheric processes by using Self-Organizing Maps (SOMs).
    A. SOMs are created for daily mean surface level atmospheric variables using 6, 12, and 18 nodes for initial investigation. The goals of this step are to understand what atmospheric variables show association with soil moisture defined flash droughts, what size of SOM is best fit for the data, and what variables and patterns to continue to explore. Additionally, this investigation assessed whether flash drought initialization could be predicted at the daily time scale.
    B. Rather than using daily mean data, ERA5 atmospheric data, soil moisture deficit data, and EDDI data are calculated on 5-day running means (with leap days

removed from the datasets). The SOMs are then modeled using the 5-day running means (e.g. pentads) of each data variable, and the 5-day mean flash drought soil moisture deficit data.

C. The pentad-scale SOMs are analyzed, and the most interesting singular nodes from these SOMS are further assessed using a 6-node nested SOM. This nested SOM is created to better understand the patterns associated within the most significant patterns associated with flash drought.

D. SOMs of the most interesting atmospheric variables are then created with EDDI at the pentad-scale to assess how EDDI captures flash drought initialization with these atmospheric patterns.

3.2 Study Area and Time Period

The main area of interest for this research is the island of Puerto Rico; however, to properly analyze the antecedent and concurrent synoptic meteorological conditions associated with flash drought, the domain extends further into the tropical Atlantic Ocean and Caribbean. Due to kinematic and thermodynamic forcings introduced by the Saharan Air Layer (e.g. Mote et al. 2017), the eastern part of the domain extends to Africa in some parts of the analysis. The tropical domain is especially important because flash drought has been studied for the Continental United States far more than for Puerto Rico, despite devastating impacts from flash drought events. Major risks for the island when experiencing a flash drought event include a depletion of municipal water supply, environmental degradation of the biodiverse ecosystem in the El Yunque Rain Forest, and the cascading financial burdens associated with these impacts (Beard et al., 2005; Burrowes et al., 2004; Chen et al., 2019; Covich et al., 2003; Mote et al., 2017; Otkin et al., 2016). The island's unique topography and physical geography provides for varying microscale and synoptic scale weather conditions due to the varying elevation and biota across the island (Figure 3.1).

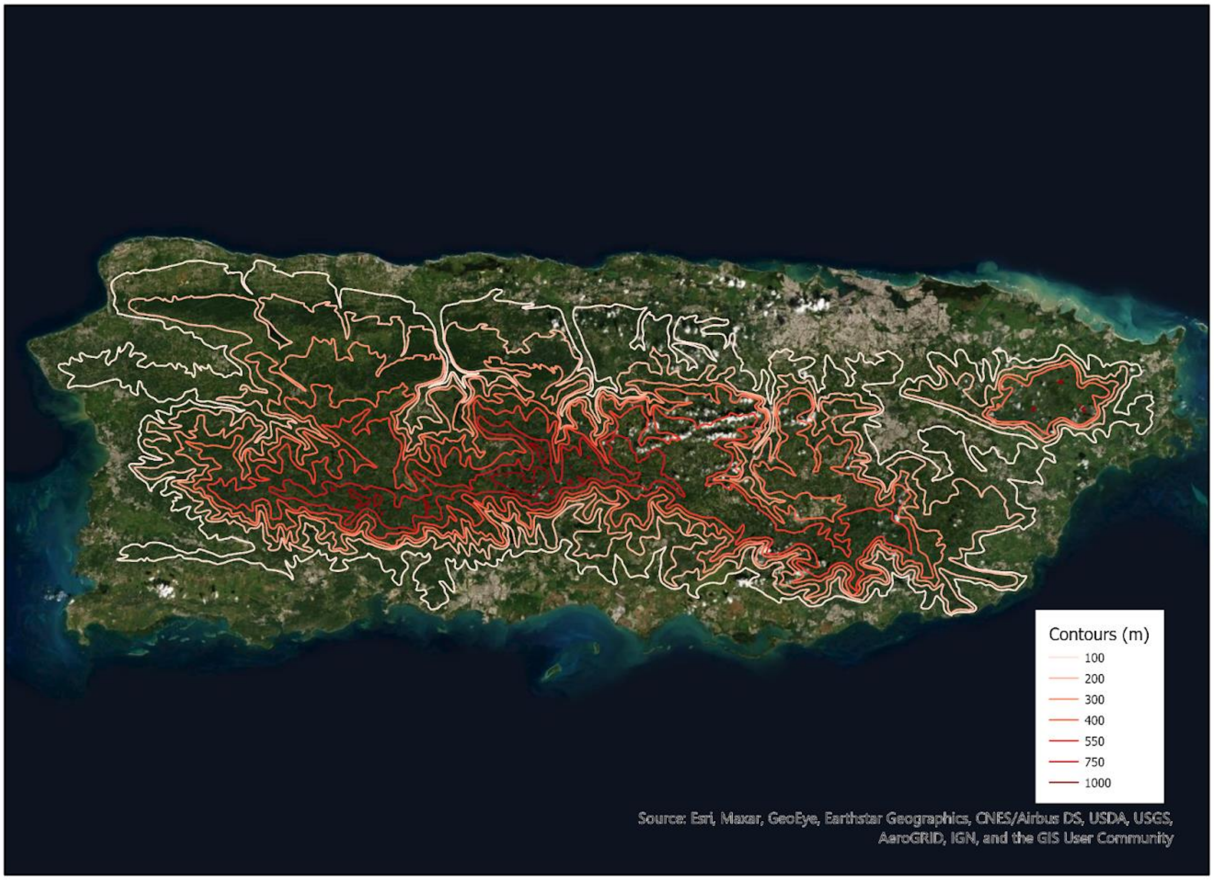


Figure 3.1: Map of Puerto Rico with ESRI Imagery base map and contour lines in meters.

The temporal range of this study is limited by data availability; however, there is still plenty of data for high quality analysis. The Global Land Data Assimilation System (GLDAS) data, which provides soil moisture anomalies used in one of the flash drought definitions leveraged in this study, dates to 2000. Preliminary analysis of flash drought initiation and onset using soil moisture is completed for the years 2000 to 2020. The European Centre for Medium-Range Weather Forecasts (ECMWF) maintains and organizes the reanalysis data leveraged in this study. The

ECMWF Reanalysis 5th Generation (ERA5) reanalysis data is used to get a better understanding of the other variables involved in environments conducive to flash drought dating back to 1981.

3.3 Data

Reanalysis data are imperative for studying past weather and climate in any part of the world. These data include wind speed and direction, temperature, humidity, pressure, and many more atmospheric variables daily. Reanalysis blends observations with past weather forecasts as well as modern modeling techniques to produce a comprehensive picture of the data. By blending these products together, gaps in observations can be accurately and reliably filled to better understand weather and climate patterns. While there are many different reanalysis packages available, each has their strengths and weaknesses. Several land and atmospheric reanalysis data sources were considered including GLDAS, ERA5-Land, ERA5, NCEP-NCAR or NASA's MERRA-2. Ultimately, ERA5 was selected for the atmospheric data due to those data being produced with the most sophisticated data assimilation scheme and with the highest vertical and horizontal resolution of the available global reanalysis datasets (Hersbach et al., 2020). One of the flash drought definitions, calculated using soil moisture anomalies, leveraged GLDAS soil moisture data. Lastly, EDDI was calculated using a suite of variables from ERA5-Land reanalysis product, which was released in Fall 2021.

Currently, ERA5 is one of the most prominent reanalysis products for weather and climate research, replacing ERA-Interim only in the past couple of years. The European Centre for Medium-Range Weather Forecasts (ECMWF) produced the ERA5 reanalysis product and is housed under the Copernicus Climate Change Service (C3S) (Hersbach et al., 2020). The atmospheric reanalyses produced by ECMWF have gone through a few phases. Beginning in the early 1980's, FGGE was the first atmospheric reanalysis data for just the year 1979 at a 208 km grid resolution. These reanalyses incrementally improved over the years from FGGE to ERA-15, ERA-40, ERA-Interim, and lastly ERA5. The ERA5 reanalysis incorporates a detailed record of the global atmosphere, land surface and ocean waves from 1950 to current day (Hersbach et al., 2020). ERA5 greatly improves on ERA-Interim in a few ways. First, ERA-Interim only spanned from 1979 to 2019. Also, the horizontal resolution has been greatly enhanced from 80 km in ERA-Interim to 31 km in ERA5. ERA5 also includes hourly outputs throughout the reanalysis while ERA-Interim includes 6-hourly outputs for analyses and 3-hourly for forecasts (Hersbach et al., 2020). The enhanced temporal and spatial resolution and quantity of data in ERA5 over ERA-Interim provides an excellent dataset for improved weather and climate research.

One of the other key data sources for this study is the GLDAS observational products, which are developed and maintained by NASA. These data will specifically provide modeled and observed soil moisture, temperature inversion, pressure, wind speed and direction, and evapotranspiration (ET) for Puerto Rico. Soil moisture data is especially important for this study as the indicator of a flash drought event, while the atmospheric variables help to describe the circumstances of how the event occurred. Along with GLDAS, ERA5-Land is an excellent source of surface level reanalysis data.

ERA5-Land is provided by ECMWF and was released in Fall 2021. Because these data were released during the time this study was conducted, it provided a unique opportunity to change the methodology slightly to incorporate these data. ERA5-Land is high resolution data at approximately 9 km spatial resolution on an hourly time scale. These data are an hourly replay of the land component of ERA5 on a much finer scale (9 km from 31 km) (Giusti, 2020). The improved spatial and temporal resolution of ERA5-Land allows for deeper quantitative analysis of the reanalysis atmospheric variables for Puerto Rico and the Caribbean.

3.4 Methods

The methodology for this research leverages the GLDAS soil moisture data to first define flash drought events in Puerto Rico. While there is no uniform flash drought definition, many definitions use a soil moisture deficit over a certain time period. The definition used in this study is based on the Ford & Labosier 2017 study, which defined a flash drought event as a situation where soil moisture percentiles drop from above the 40th percentile to below the 20th percentile over a 20-day period at a given location. GLDAS provides the 10-40 cm soil moisture data for this analysis in Puerto Rico. While GLDAS also provides the 0-10 cm soil moisture data, these data were found to be overly sensitive to the flash drought index defined for this study. This methodology uses soil moisture percentiles over a time period to assess the rate of intensification, so more intense flash droughts would have a more drastic drop in soil moisture. While there exist flash drought definitions that focus more on the duration of the flash drought event rather than the rate of intensification, there is some consensus that a more prudent way to assess flash drought events is to assess the rate of intensification over a given time period because this methodology highlights the events' most damaging characteristic (Otkin et al., 2018).

Once flash drought is defined, and events are discovered dating back to 2000 (due to the temporal availability of GLDAS data) synoptic scale atmospheric drivers of flash drought are analyzed using self-organizing maps (SOMs). SOMs have been used to predict precipitation variability in the U.S. Caribbean using low-tropospheric moisture and circulation variables, and this study found that low-precipitation days are associated with atmospheric states with high 1000-700 hPa bulk wind shear and decreased 700 hPa moisture (Ramseyer & Mote, 2018). Mathematically, SOMs are an implementation and extension of artificial neural networks (ANNs). ANNs have also been used to assess precipitation variability in this study area to determine the statistical significance of multiple atmospheric predictor variables. Results from a study using ANNs for Puerto Rico found that lower tropospheric moisture and winds are physically linked to variability in sea surface temperatures (SSTs) and the strength of the North Atlantic High Pressure cell (NAHP) (Ramseyer & Mote, 2016). Lastly, the Saharan Air Layer (SAL), which is a dry, dust-rich air mass transported from the Saharan Desert of Africa to the Caribbean in the mid to upper atmosphere, has been linked to being a rainfall suppressant for Puerto Rico as well (Mote et al., 2017). The SOM methodology was chosen primarily because of its excellent capability to parse out and map atmospheric patterns, and its ability to be paired with statistical metrics by node, thus providing some explanatory power over each node and how closely associated they are with flash drought events (e.g. Sheridan and Lee 2011). Important atmospheric variables in the SOMs for this study include specific humidity, divergence, vertical velocity, temperature, U and V wind fields, and Saharan dust.

The objective of this study is to identify variability between flash drought events by comparing the similarities and differences of the synoptic scale atmospheric variables involved using a self-organizing map. This study evaluates synoptic variables and patterns that contribute to flash drought events, especially the most devastating events to enhance prediction and preparedness ahead of the events. A comprehensive table of each SOM created for this study is provided (Table 3.1).

Self-Organizing Map Methodology				
Variable	**Pressure Level**	**Nodes**	**Time Scale**	**FD Definition**
Divergence Raw Values	1000 hPa	6, 12, 18	Daily Mean	Soil Moisture
Divergence Anomalies	1000 hPa	6, 12, 18	Daily Mean	Soil Moisture
Temperature Anomalies	1000 hPa	6, 12, 18	Daily Mean	Soil Moisture
Vertical Velocity Anomalies	1000 hPa	6, 12, 18	Daily Mean	Soil Moisture
Zonal Winds	1000 hPa	6, 12, 18	Daily Mean	Soil Moisture
Meridional Winds	1000 hPa	6, 12, 18	Daily Mean	Soil Moisture
Specific Humidity Anomalies	1000 hPa	6, 12, 18	Daily Mean	Soil Moisture
Divergence Anomalies	700, 850, 1000 hPa	12	Pentad Running Mean	Soil Moisture
Temperature Anomalies	700, 850, 1000 hPa	12	Pentad Running Mean	Soil Moisture
Vertical Velocity Anomalies	700, 850, 1000 hPa	12	Pentad Running Mean	Soil Moisture
Zonal and Meridional Winds	1000 hPa each	12	Pentad Running Mean	Soil Moisture
Specific Humidity Anomalies	700, 850, 1000 hPa	12	Pentad Running Mean	Soil Moisture
Saharan Dust Aerosol Depth	550 nm	12	Pentad Running Mean	EDDI
Vertical Velocity Node 1	850 hPa	6 - Nested	Pentad Running Mean	Soil Moisture
Vertical Velocity Node 3	850 hPa	6 - Nested	Pentad Running Mean	Soil Moisture
Vertical Velocity Node 1 - No Hispaniola	850 hPa	6 - Nested	Pentad Running Mean	Soil Moisture
Vertical Velocity Node 3 - No Hispaniola	850 hPa	6 - Nested	Pentad Running Mean	Soil Moisture
Specific Humidity Node 11	700, 850 hPa	6 - Nested	Pentad Running Mean	Soil Moisture
Vertical Velocity Anomalies	850 hPa	12	Pentad Running Mean	EDDI
Relative Humidity Anomalies	850 hPa	12	Pentad Running Mean	EDDI

Table 3.1: All SOM reanalysis variables and flash drought definitions incorporated.

The SOM generates nodes in a rectangular matrix, so the three SOM analyses completed in the initial phase were six nodes (2 x 3), twelve nodes (3 x 4), and eighteen nodes (3 x 6). The SOMs are fed ERA5 data, and they are statistically linked to the flash drought events that have been identified. These events were identified using GLDAS data for the 10-40 cm soil moisture range where the soil moisture percentile dropped from an amount greater than the 40th percentile to below the 20th percentile in less than 20 days. While previous studies have generally used 10-40 cm soil moisture in the U.S. Great Plains (Ford and Labosier 2017), 0-10 cm was also considered here to maximize potential case studies; however, further analysis showed this depth to be overly sensitive to flash drought event detection.

The 10-40 cm soil moisture data is important for identifying the severity of flash drought events. Initially, the goal was to see which of the SOM nodes from the 0-10 cm data have the highest frequency of “severe” flash droughts that are also detectable in the 10-40 cm data. However, the 0-10 cm data was overly sensitive to flash drought initiation. Therefore, the 10-40 cm soil moisture data was used for flash drought detection for this study. Once the soil moisture analysis is complete, pre-processing of the ERA5 and GLDAS data will be necessary before performing the SOM analysis. These reanalysis data are multi-dimensional, but the SOM requires 2-dimensional data, so Python coding language and the Linux OS were employed to process the data for use in a SOM. The SOM analysis is conducted using a package in Matlab called SOMToolbox, which is found on this site: http://www.cis.hut.fi/somtoolbox/. Once the SOM analysis is completed, the results are analyzed and visualized in Python. The annual frequency of individual SOM nodes is analyzed for temporal changes as well.

The changes in node frequency over the 40-year study period are evaluated for statistical significance through the use of Mann-Kendall tests, which are non-parametric function tests for analyzing trends over time (Kendall, 1948; Mann, 1945). These Mann-Kendall tests were run on each node to determine whether there was a significant increasing trend, decreasing trend, or no trend using a p value = to 0.05. While the potentially most interesting results will come from the increasing or decreasing trends, all results will be shown. A statistically significant increasing trend shows that within that node, flash drought frequency is increasing over time. The opposite is shown for the decreasing trend, and no trend signifies no statistically significant trend is shown. No trend is common throughout these results, which is partially due to the sample size being reduced in certain nodes to incorporate too little data for a statistically significant trend.

Lastly, the climatology of synoptic forcings elucidated by the SOM are extended to 1981, which allows for a longer temporal analysis of the frequency of the synoptic types responsible for flash drought. This 40-year climatology also allows for analysis on the long-term trends in node frequencies. The data were downloaded from ECMWF by single level and by pressure level on a daily time scale as NetCDF files. These files were manipulated and compiled as daily means by atmospheric variable for 1981 to 2020 to be fed into a SOM for surface-level analysis (Table 3.1). Once SOMs were created and analyzed for those surface-level variables, the data was again manipulated to pentad-scale. These data were compiled as 5-day running means (e.g. pentads) and analyzed by pressure level and atmospheric variable. In some cases in these analyses, the region of Hispaniola (West of Puerto Rico) caused noise in the data due to the elevation of the land mass, so some of the data were spatially constrained to exclude areas west of Puerto Rico and address the elevation issues. Additionally, by constraining the data to areas east of Hispaniola, we focus on the upwind climate forcing on the U.S. Caribbean. There are very few instances (<1% of days) where the U.S. Caribbean experiences a westerly wind. This step makes sense because the predominant wind direction in the Tropics that are associated with atmospheric patterns come from the East, which is what this study is looking for. Each of the SOM figures incorporated a Mann-Kendall statistical analysis or a calculation of flash drought days per node.

Chapter 4: Results and Discussion

4.1 Initial Soil Moisture Flash Drought Calculation

At the beginning of this study, flash droughts were calculated and visualized using the soil moisture definition, leveraging GLDAS data, to understand how many events occurred from 2000 to 2020. These flash drought events are determined by the soil moisture percentile. For a flash drought event to be defined, there must be a decrease in soil moisture from above the 40th percentile to below the 20th percentile in less than 20 days. This definition is subject to some noise where a flash drought was defined for a day or two, but was quickly dissipated, so an additional parameter was added to reduce this noise. The soil moisture decrease must sustain for 10 days to be considered a flash drought event.

Figure 4.1: Flash drought days defined by soil moisture deficit from 2000 to 2020 using GLDAS soil moisture data. The colors indicate the decrease in soil moisture percentile.

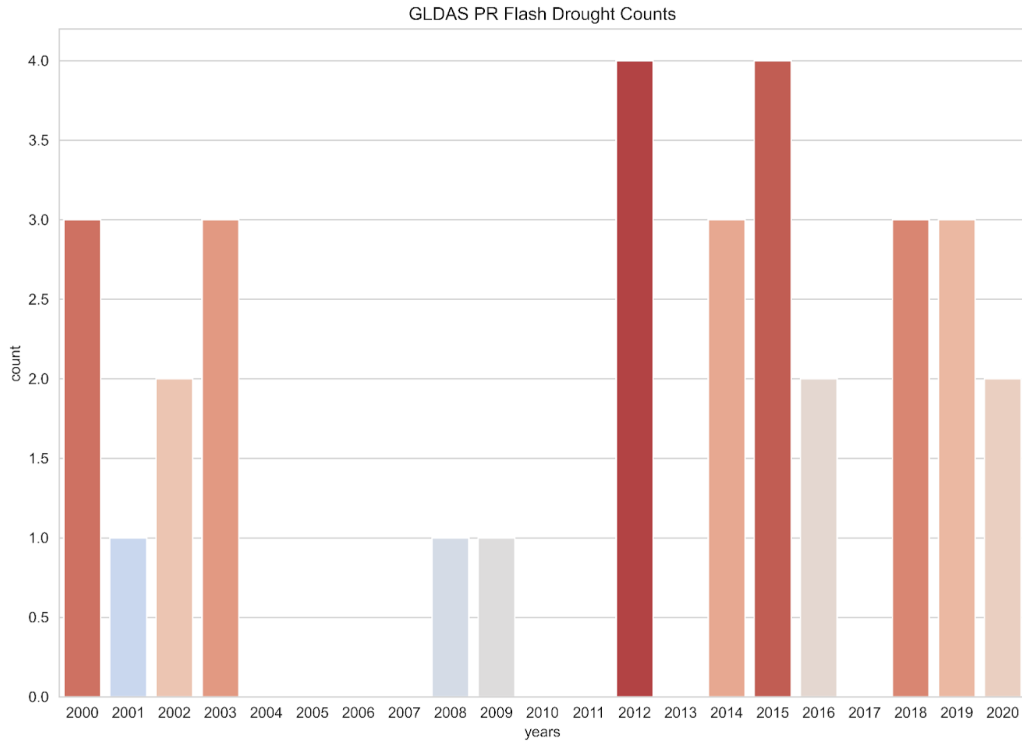


Figure 4.2: Histogram of total flash drought events from Figure 4.1.

This initial investigation provided an interesting insight to how flash drought has affected Puerto Rico over the last twenty years. The clear break in flash drought from 2004 to 2011, with a major resurgence from 2012 to 2020, indicates that flash droughts may have a decadal, oscillatory time scale. More research is needed to further understand how and why flash droughts may occur in phases like the ones shown in Figures 4.1 and 4.2. While adding the additional parameter reduced some of the sensitivity in the flash drought calculations, these are still most likely an overestimation as well as a prolonged period that is reminiscent of drought, rather than flash drought. There are potential cases where temporary recharges in soil moisture occurred that caused soil moisture anomalies to briefly rebound, only to resume drying again. These small breaks therefore initiated a “new” flash drought event that may only be a continuation from the initial flash drought event.

4.2 SOMs of Daily Atmospheric Variables

Divergence, temperature, vertical velocity, u- and v- winds, Saharan dust, and specific humidity were analyzed using SOMs to understand if they play a role in flash drought initiation and/or intensity for Puerto Rico and the Caribbean. Each of these variables provided a variety of intriguing results. SOMs were created using six, twelve, and eighteen nodes for daily values and twelve nodes for five day rolling mean values. These SOMs were created using a few domains and all daily ERA5 data from 1981 to 2020. All the SOMs presented here were trained using gradient-descent minimization for 1000 epochs using a hexagonal lattice structure.

For the first training of SOMs, the reanalysis data were aggregated to daily values at the 1000 hPa level to better understand what atmospheric variables at the surface level would show patterns associated with flash droughts. These were the first SOMs created to get an idea of the best size of SOM, the most interesting variables, and what patterns to continue to explore. Additionally, it allowed for investigation into whether flash drought initialization could be predicted at the daily time scale. As previously discussed, drought in the Caribbean can evolve on the order of days. Each of these SOMs were plotted with a Mann-Kendall trend analysis using the yearly frequencies of each node. Each node was analyzed for an increasing or decreasing trend based on a p value of 0.05.

The first set of daily SOMs will show the six, twelve, and eighteen node map configurations to provide evidence for why the twelve node maps were ultimately selected as the best option for resolving the distribution of the data space. The first variable studied for this analysis was 1000 hPa level divergence and divergence anomalies to determine which node map sizes best resolve the data space.

4.2.1 Divergence

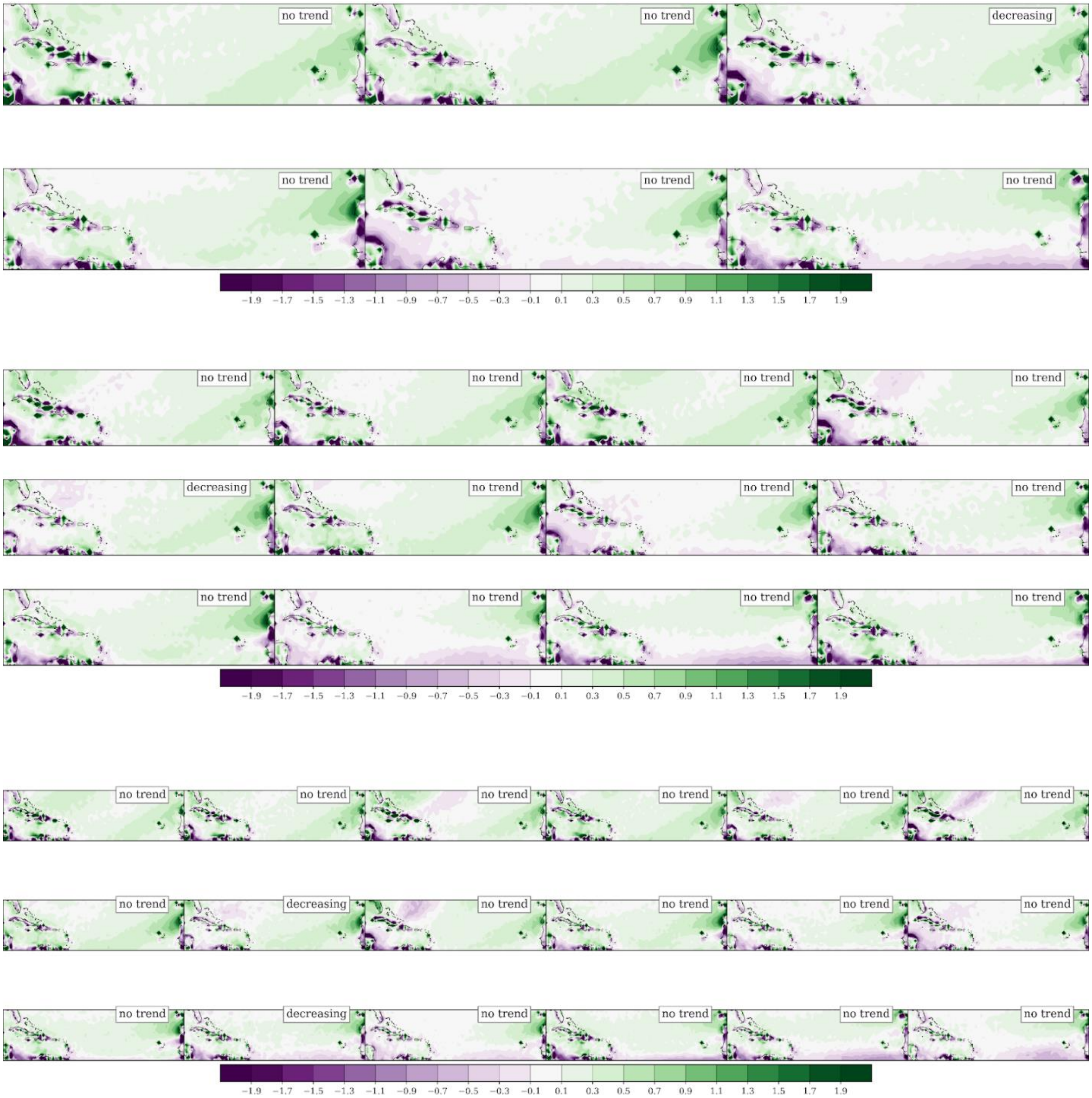
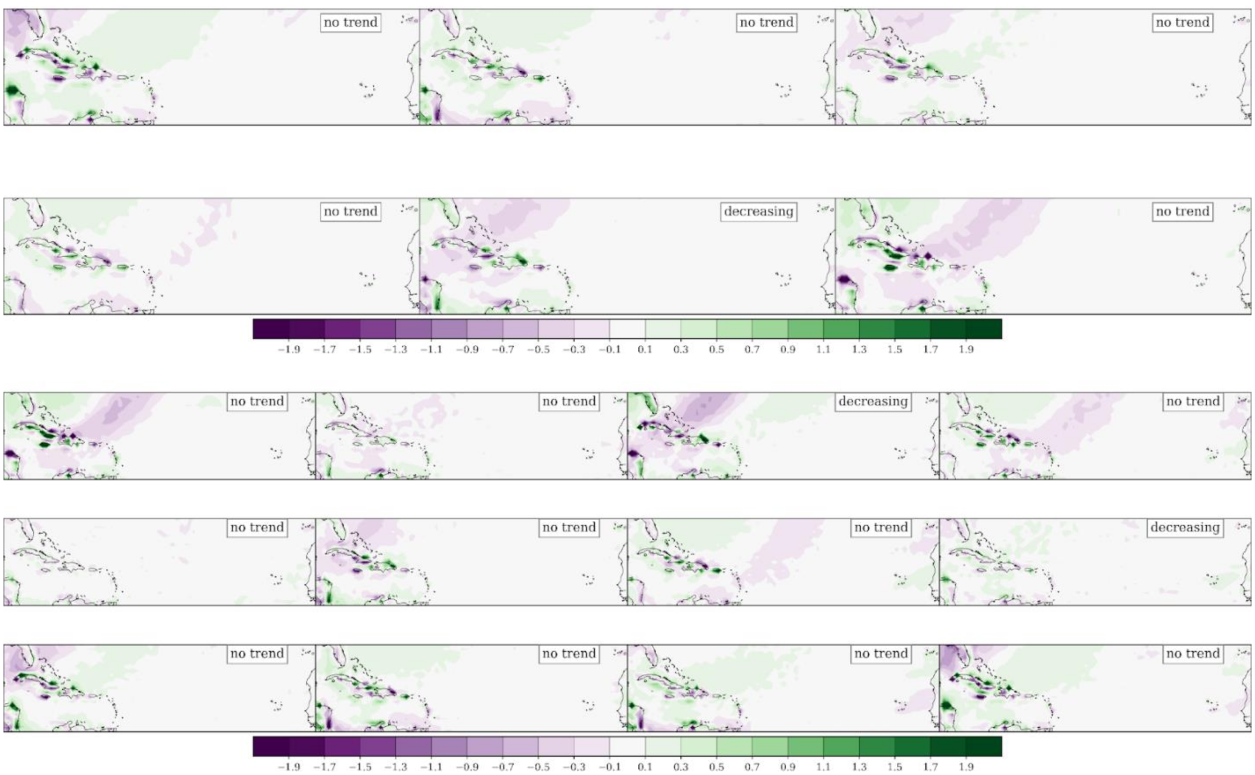


Figure 4.3: Daily Divergence Values (s^{-1}*10) at 1000 hPa for 6, 12, and 18 node SOMs.

The domain for these figures extends from Florida to the west coast of Africa because we wanted to see how these patterns are taking form across the Atlantic Ocean toward the Tropics. First, notice the trend analysis showing a few decreasing trends in a couple of the nodes, but there are not many spatial patterns of significance showcased here. Also, note the eighteen node SOM failing to cluster the data in a meaningful way, which is a pattern seen throughout the other eighteen node SOMs. The eighteen node SOM frequently shows duplicate nodes that seem to try and resolve the same divergence pattern, which suggests that eighteen is too many for this type of analysis. The six node SOM does a decent job of showing some patterns, but the data itself does not seem to show much in general here.

4.2.2 Divergence Anomalies



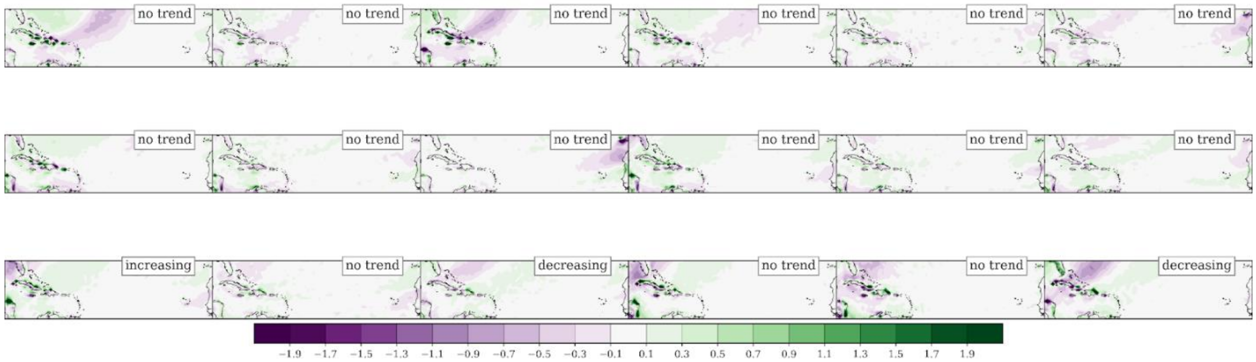
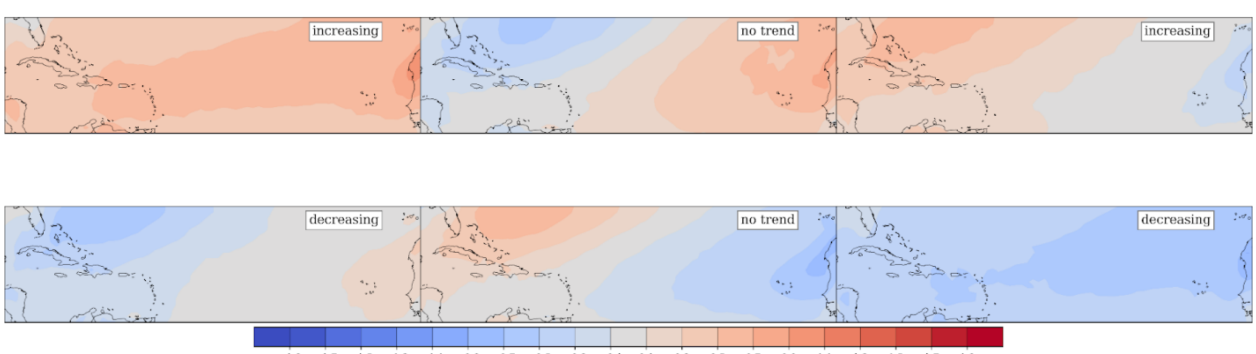


Figure 4.4: Daily Divergence Anomaly Values (s^{-1}*10) at 1000 hPa for 6, 12, and 18 node SOMs.

By looking at the data in anomalies rather than raw values, more interesting patterns are shown. First, there is not much data shown in the Atlantic Ocean ahead of Puerto Rico, but some patterns appear west of Puerto Rico. These patterns show parallel streaks of convergence (purple) and divergence (green), which could be of some interest at a more localized scale. The eighteen node SOM have a few nodes that look very similar, but the difference between node one (top left) and node eighteen (bottom right) show the SOM can parse out these opposing patterns. Again, the trend analysis here does not show much, but these patterns start to give additional confidence that the SOM is able to depict atmospheric patterns well.

4.2.3 Temperature Anomalies



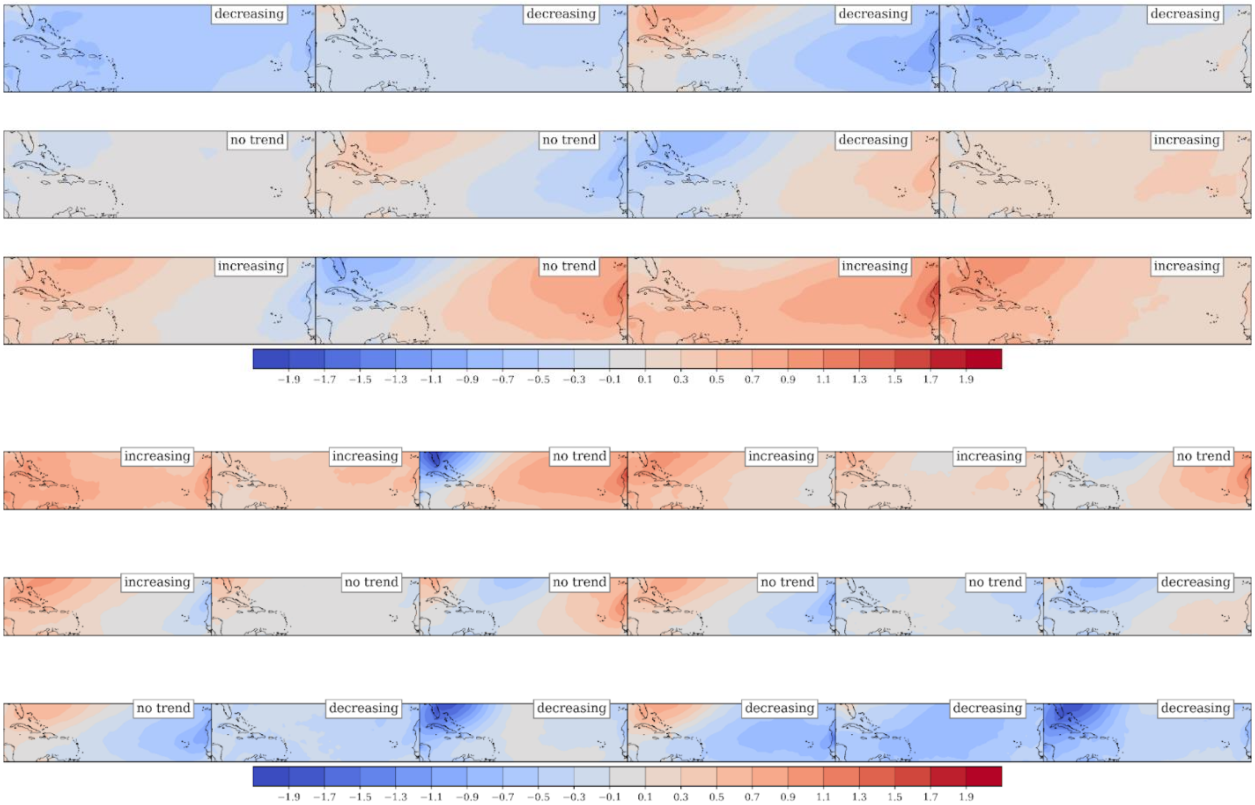


Figure 4.5: Daily Mean Temperature Anomalies (K) at 1000 hPa for 6, 12, and 18 node SOMs.

Temperatures in the tropics vary less overall than in more temperate regions; however, seeing higher anomalies consistently reporting increasing frequency over time and lower anomalies showing the opposite throughout each of the SOMs is an interesting discovery. Higher temperatures are typically associated with drought due to its role in depleting soil moisture through increasing evapotranspiration, especially with the higher amount of insolation in the tropics. Node one specifically in the six node SOM shows a clear path of higher temperatures directly from the west coast of Africa, so these atmospheric patterns should be further tested for any possible association with the Saharan Air Layer.

4.2.4 Vertical Velocity Anomalies

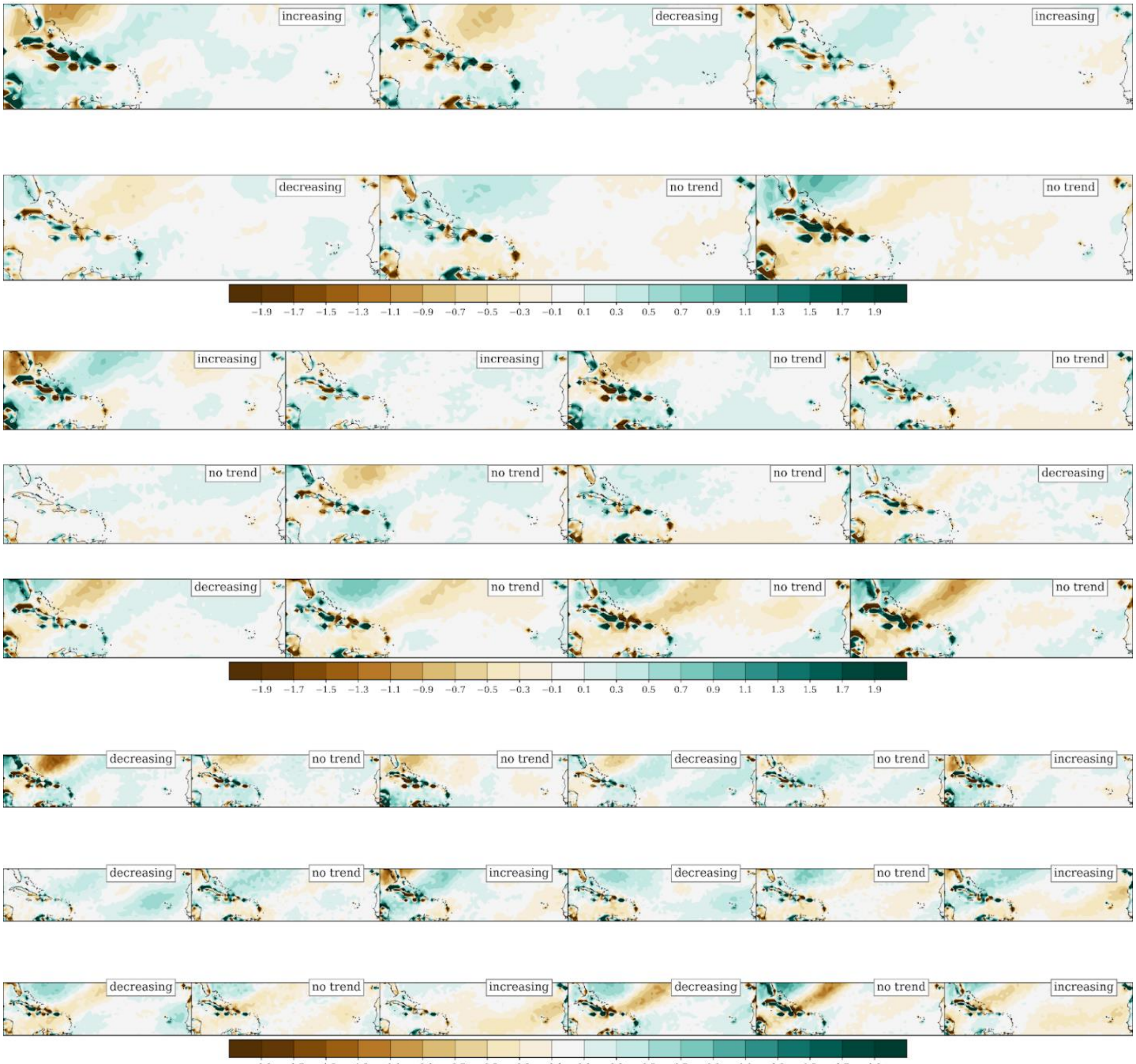


Figure 4.6: Daily Mean Vertical Velocity Anomalies (Pa s^{-1}*10) at 1000 hPa for 6, 12, and 18 node SOMs.

There are clear streaks of opposing vertical velocity anomalies west of Puerto Rico through Figure 4.6. Compared to previous figures, the trend analysis is finding a few more increasing and decreasing frequencies; however, the patterns themselves are difficult to properly analyze. These figures show some interesting patterns, but the amount of noise associated with the Hispaniola region makes the analysis harder. This noise is driven primarily by the highest elevations of Hispaniola, which tend to be resolving vertical velocity on pressure surfaces that are occurring beneath the land surface of the mountainous regions. By constraining the domain and data down to Puerto Rico and data points eastward, vertical velocity can be better understood for its association with Puerto Rico.

4.2.5 Zonal Winds

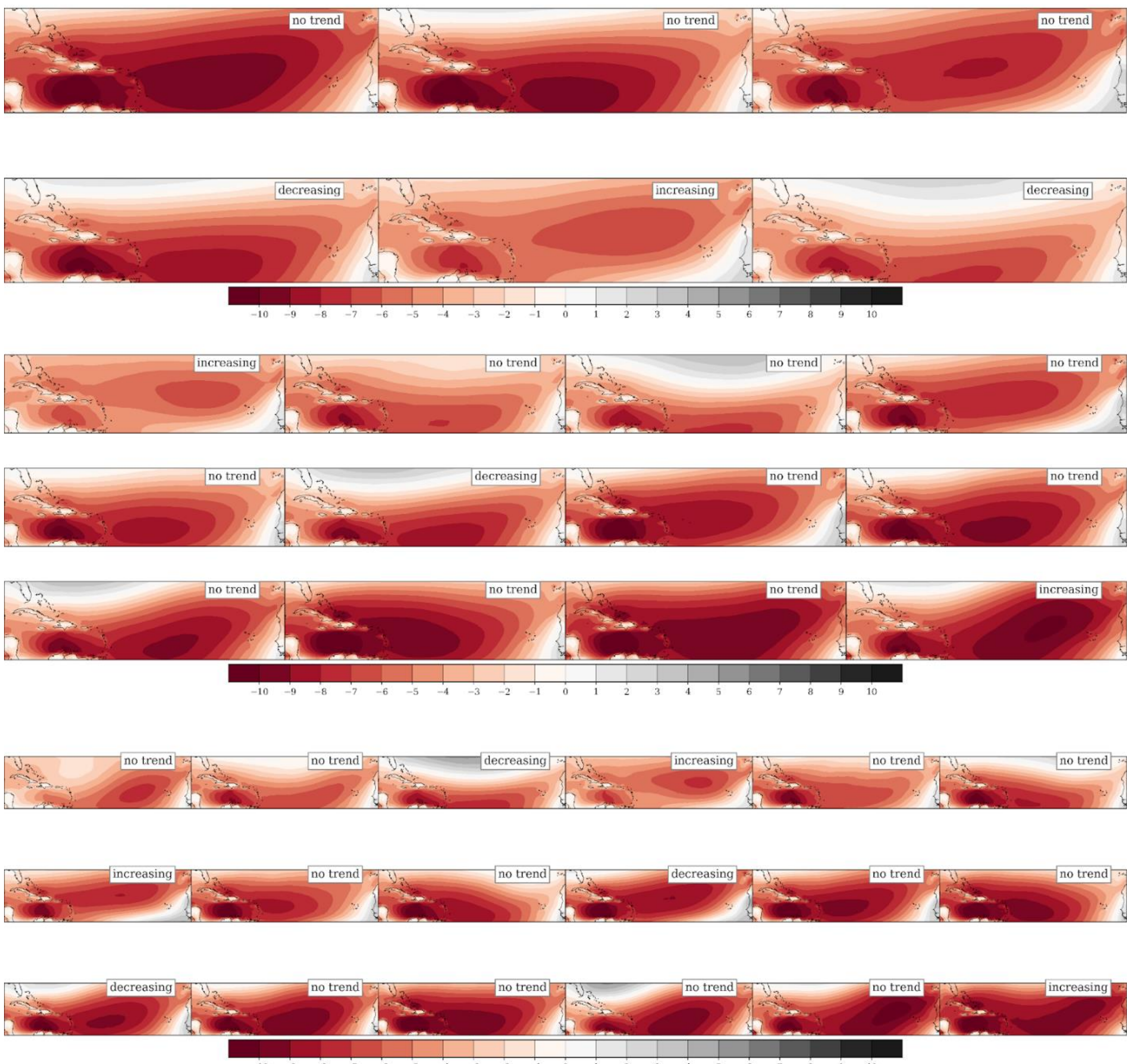
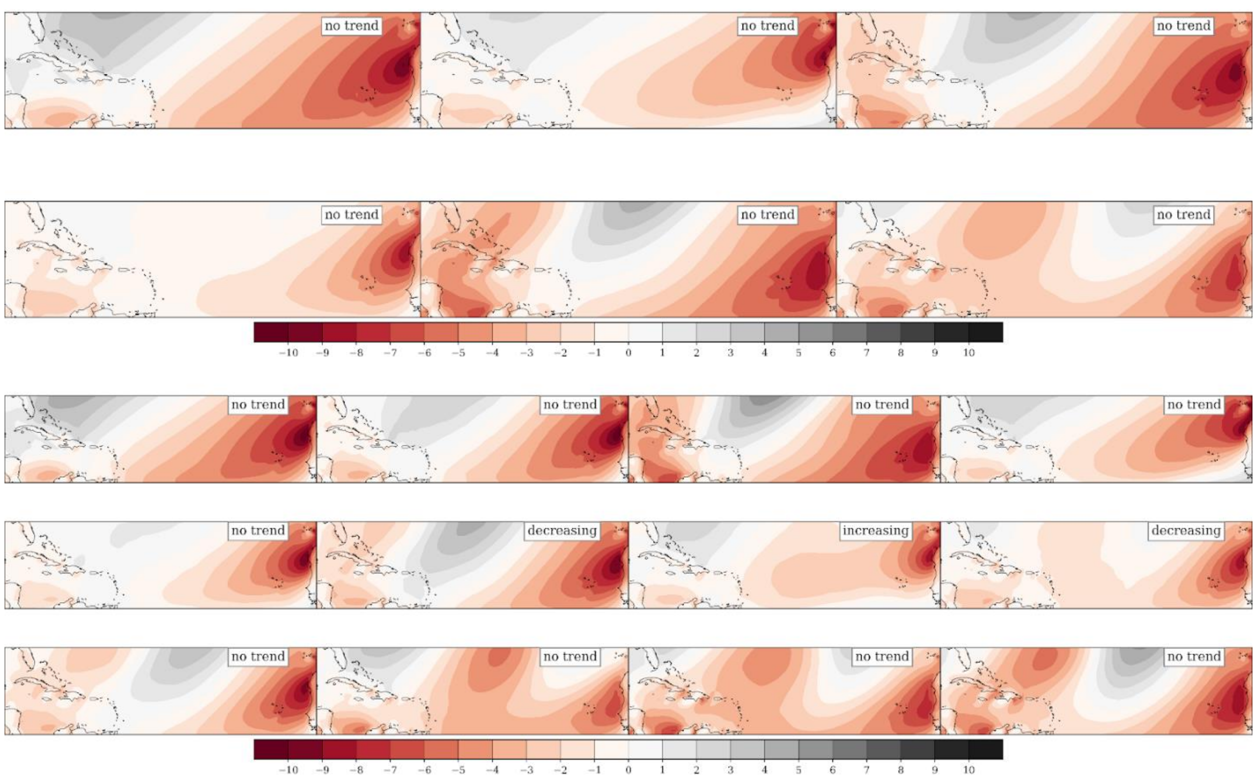


Figure 4.7: Daily Mean U Wind Values (m s^{-1}) at 1000 hPa for 6, 12, and 18 node SOMs.

The zonal wind, otherwise known as the u-component of the wind, largely runs from east to west in the Tropics. These winds are the easterly trade winds, which drive hurricane paths across the Atlantic Ocean, up the Tropics, and up to the mid-latitudes where the wind shifts to westerlies. This pattern also explains why so much of the map is red: the westerlies are negative values, and in a domain this large, it is very hard to understand the regional impact these winds are making on Puerto Rico itself. It is possible that nodes with a weaker gradient could potentially contribute to some flash drought if associated with lack of moisture as well, but that would need to be further explored. Despite the lack of clear patterns associated with flash drought, these figures again validate the SOM can properly parse the data.

4.2.6 Meridional Winds



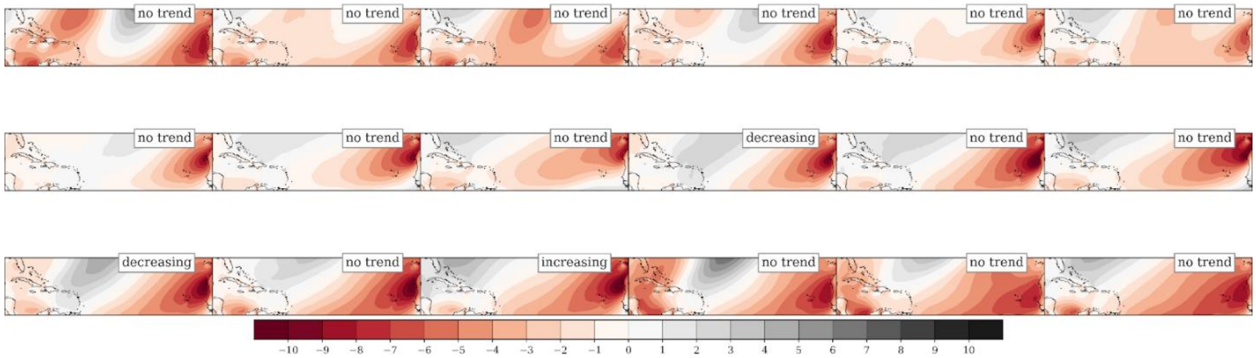


Figure 4.8: Daily Mean V Wind Values (m s^{-1}) at 1000 hPa for 6, 12, and 18 node SOMs.

Converse to the zonal wind, the meridional wind, or the v-component of the wind, shows the North-South component of the wind. At this latitude, much of the wind blows from North to South (e.g. negative values) so there is a lot of noise on the west coast of Africa where the wind is "slamming" into the continent. This may also be driven in part by the monsoonal circulation of West Africa. The wind pattern does consistently show how it blows from the North on the eastern side of the Atlantic, but at the tropics, winds push back up to the North, which makes sense in accordance with the previous hurricane track example. The six node SOM in this figure shows variation of the meridional wind patterns very well. The pattern itself is quite consistent; however, it shifts some east and west in the domain. The pattern of these meridional winds is physically consistent with the variability of the Bermuda High. Future research will be conducted to confirm this association. While the trend analysis did not find much correlation, these shifts in the domain could be of interest in further research whether they are associated with drought or the Saharan Air Layer's movement.

4.2.7 Specific Humidity Anomalies

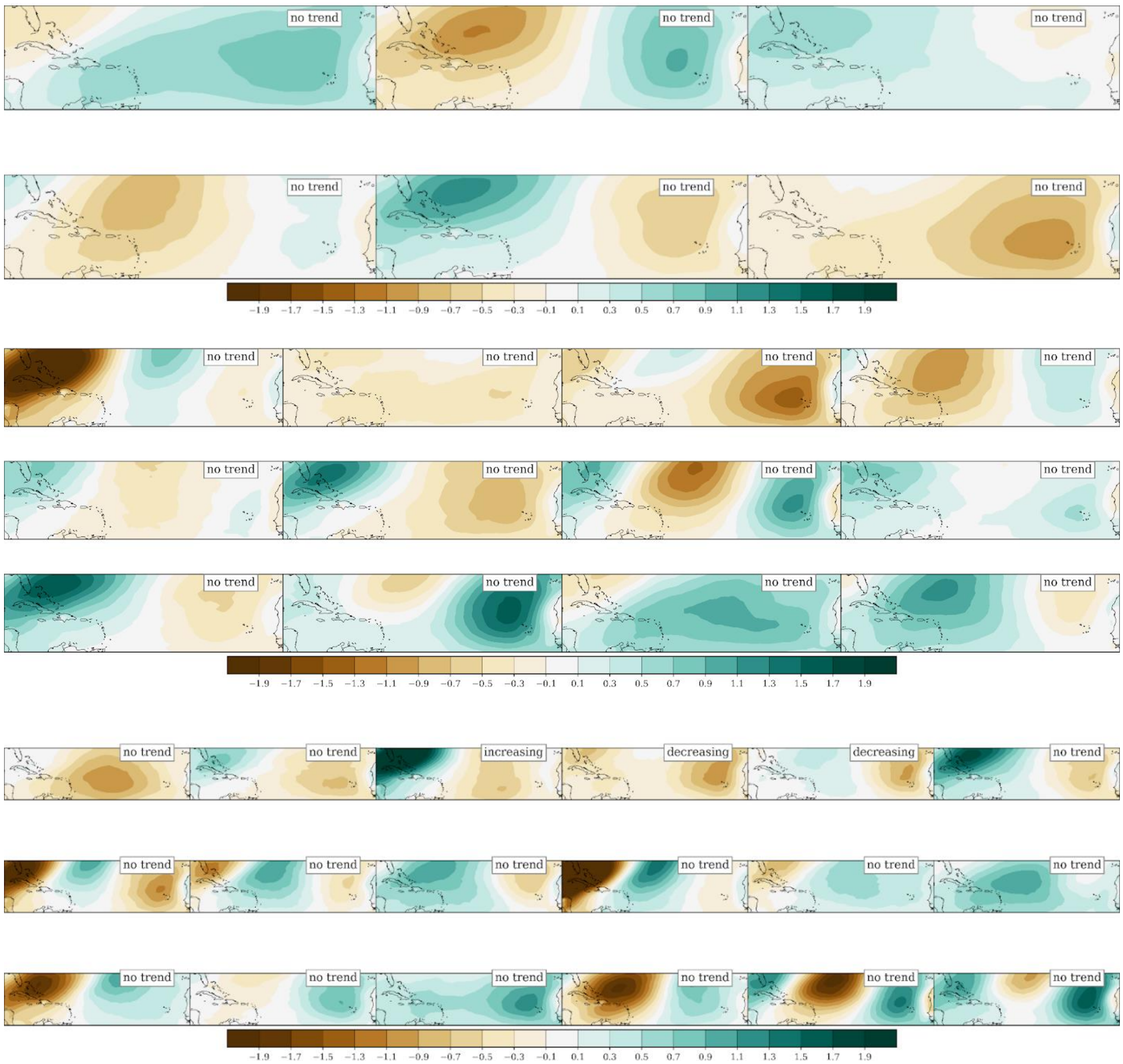


Figure 4.9: Daily Mean Specific Humidity Anomalies (kg kg^{-1}*10) at 1000 hPa for 6, 12, and 18 node SOMs.

These SOMs show some of the clearest atmospheric patterns overall. While the Mann-Kendall trend analysis largely failed to find much increase or decrease in patterns over time, these patterns cannot be overlooked. Extreme dry anomalies are an excellent indicator of drought, especially if that air mass persists for an extended period, so more work needs to be done to discover if these patterns influence flash drought specifically.

Because flash drought is associated with an approximate two-to-three-week time period, daily values may not tell the whole story. To better evaluate atmospheric forcing mechanisms on flash drought, a longer-time scale is deemed to be more appropriate. The ERA5 atmospheric data were aggregated into five-day (pentad) means to better capture the synoptic scale variability. Five day mean values of each of these variables are mapped to twelve node SOMs since twelve node SOMs were shown in Figures 4.3-4.9 to sufficiently resolve the atmospheric data variables space. While some of these SOMs revealed statistically significant trends in the data, analyses of the future impact of these trends will be addressed as future research.

4.3 SOMs of 5 Day Running Means of Atmospheric Variables

The daily analyses, in general, were difficult to detect causal atmospheric forcing. This was most likely due to a lag of greater than 1 day between the atmospheric forcing and the drought metric response (i.e. soil moisture). An additional complication of using the daily data was that some persistence in atmospheric forcing is likely necessary to initiate a flash drought.

To alleviate the aforementioned issues with using daily data for these analyses, the ERA5 atmospheric data and EDDI data were calculated on 5-day running means (with leap days removed from the datasets). In this section, the SOMs are modeling the 5-day running means (e.g. pentads) of each data variable, and the 5-day mean flash drought data. Rather than analyzing the Mann-Kendall trend for each of these nodes, the 5-day running mean SOM nodes included a different soil moisture defined flash drought metric. For each node, the map shows the average pattern generated by the SOM along with a number that corresponds to the percentage of flash drought days within that node. For example, if the number in the node is 0.1, then 10% of the days mapped to that node are considered part of a flash drought event. Each of these SOMs were also created with a smaller domain to eliminate some of the noise from Africa, as shown in the figures in the previous section.

4.3.1 Divergence Anomalies

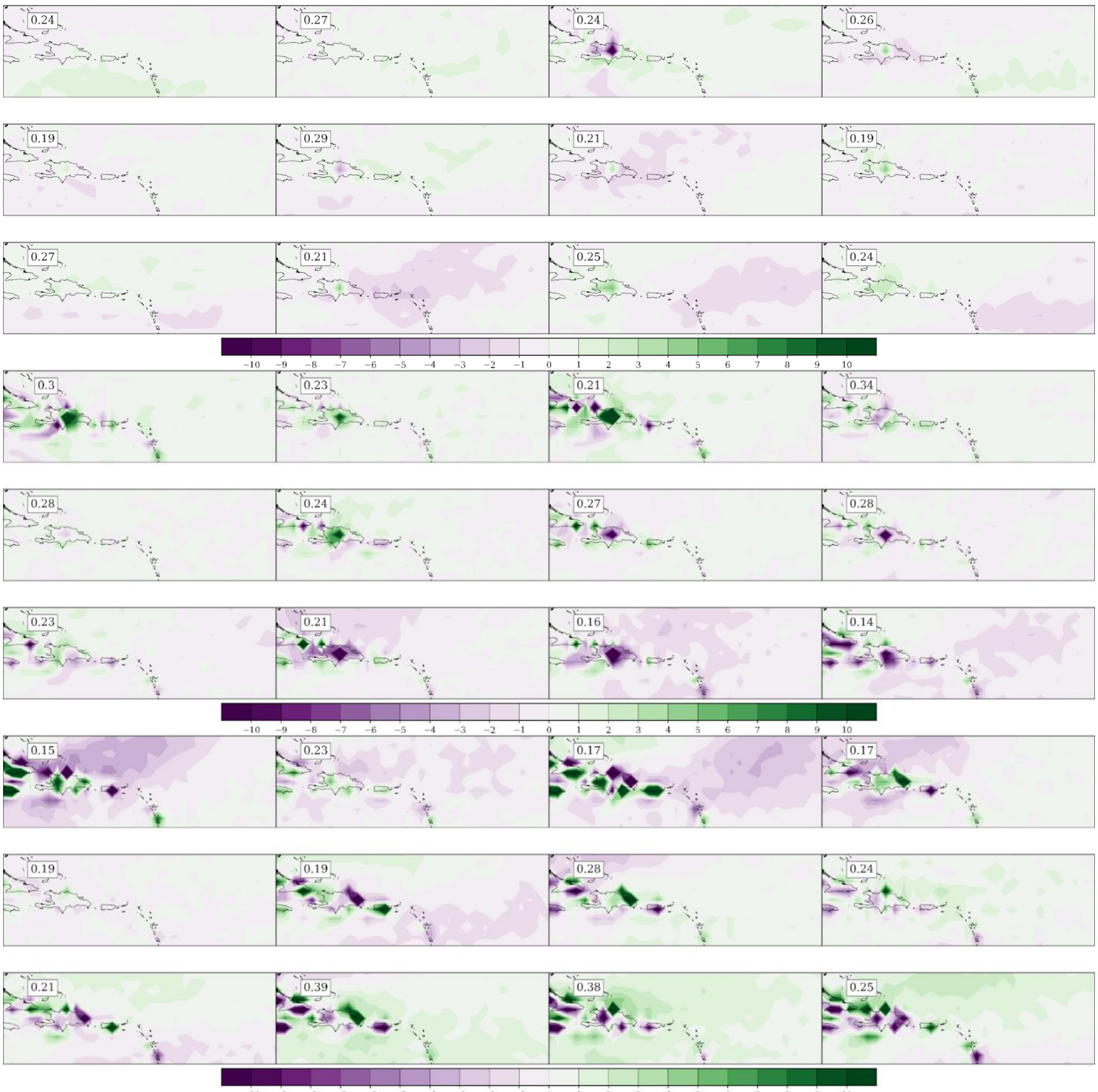


Figure 4.10: 5-Day Mean Divergence Anomalies (s^{-1}*10,000) at 700 (top), 850 (middle), and 1000 (bottom) hPa for a 12-node SOM.

One of the most obvious characteristics of these SOMs is the amount of noise coming from land masses. The divergence anomalies are skewed in either direction due to the differences in land air interactions vs. open water air interactions. Primarily, much of the noise is potentially driven by topographic issues where the pressure surface is beneath the land surface. Nonetheless, there are still some interesting findings here. The number in the upper-left hand corner of figure 4.10 corresponds with the frequency of the 5-day periods that map to flash drought days according to the GLDAS soil moisture definition. This decimal number corresponds to the percentage of days that were part of a flash drought within the node. The range of values for the percent flash drought metric primarily fall into three bins. Less than 0.20 are low frequency, 0.20 to 0.30 are more of a medium/neutral frequency, and greater than 0.30, especially into the 0.40 territory, are higher frequency. Most of the nodes in these SOMs have low explanatory power (i.e. most nodes have similar values suggesting the flash drought days are randomly distributed). The surface divergence numbers show some increasing variability amongst the nodes, suggesting that divergence and flash drought could be related. Nodes ten and eleven in the 1000 hPa SOM (Figure 4.10 - bottom) have higher frequency and nodes one, three, and four have lower frequency. While some patterns do appear, the amount of noise in the Hispaniola region makes it difficult to understand what larger scale patterns are truly showing. It is important to note that the noise introduced by Hispaniola also stretches the distribution of the data space which makes the SOM node vectors attempt to fit that stretched data space. In other words, the SOM is trying to model the noise and unable to resolve the other variability existing in the spatial domain.

4.3.2 Temperature Anomalies

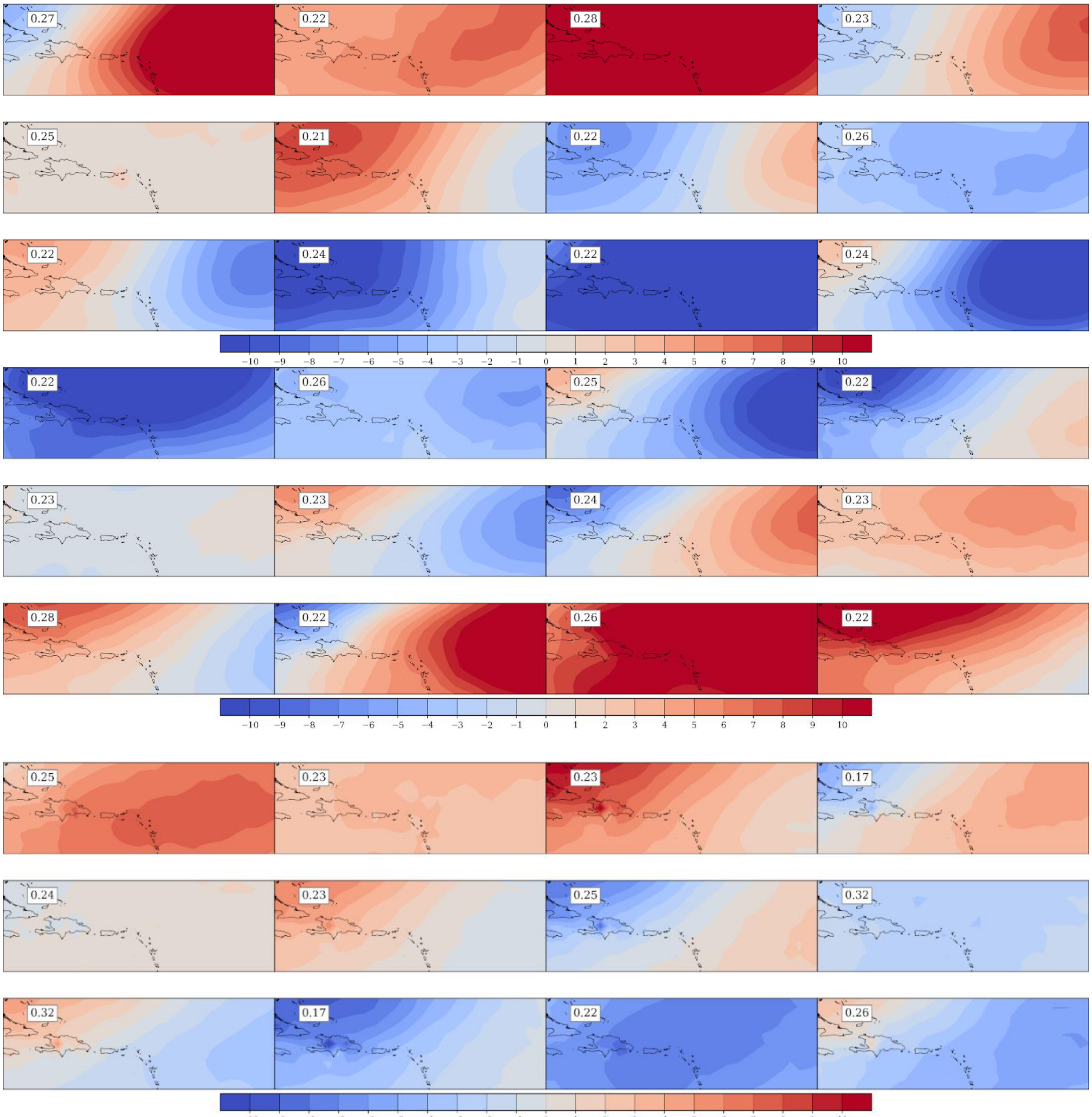
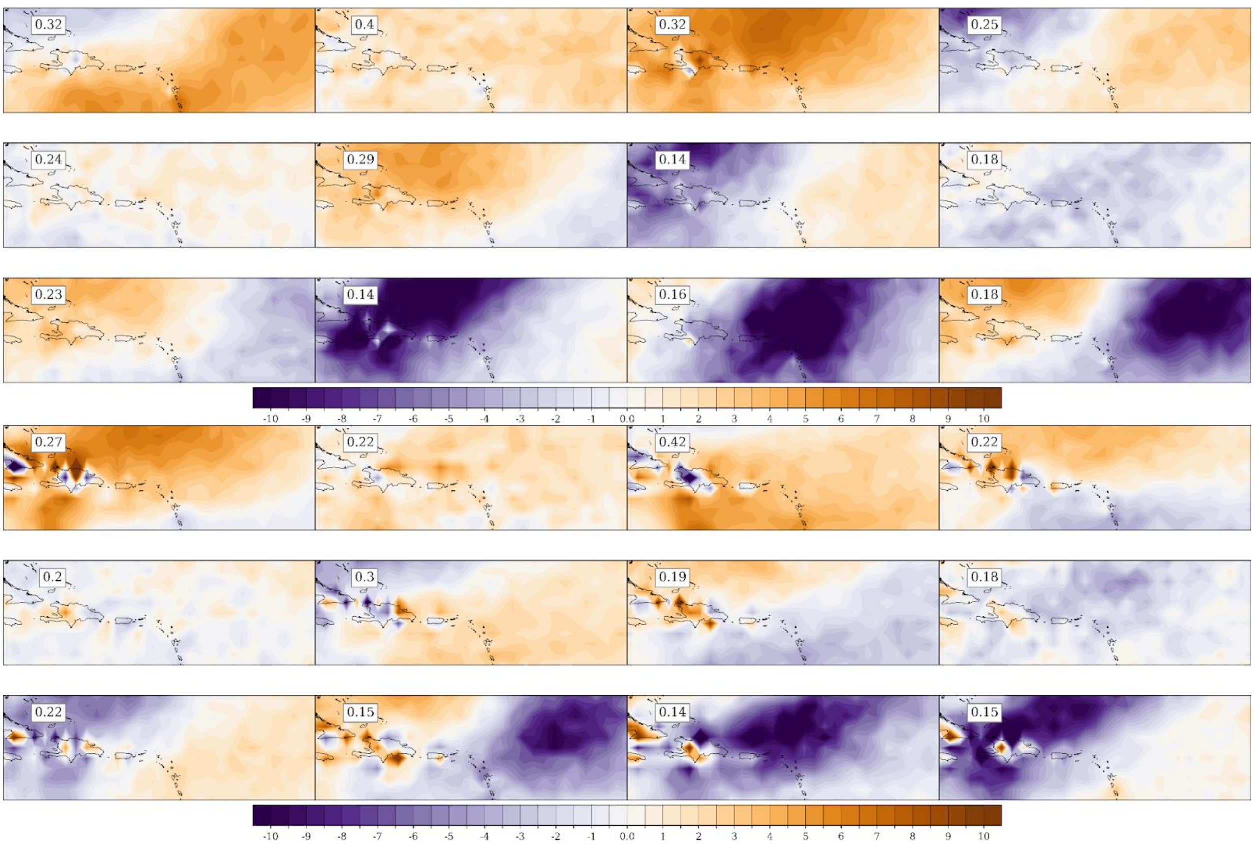


Figure 4.11: 5-Day Mean Temperature Anomalies at ($K*10^{-2}$) 700 (top), 850 (middle), and 1000 (bottom) hPa for a 12-node SOM.

The temperature SOMs showed the least significant patterns in terms of flash drought. Typically, higher temperatures would certainly accelerate drought or potentially exacerbate it, but for the tropics, the temperature anomalies may not be strong enough to make a substantial difference. This region is consistently warm with less variability than the mid latitudes, so it is understandable that temperature anomalies may not show much direct significance in flash drought initiation. Warm temperatures can contribute to drought by increasing evaporative demand and soil moisture depletion, but in the same way, warm temperatures can also contribute to instability in the atmosphere, causing precipitation to recharge the soil. While there were clear warm and cool sectors in the anomalies, there did not appear to be clear indications that they contributed to flash drought.

4.3.3 Vertical Velocity Anomalies



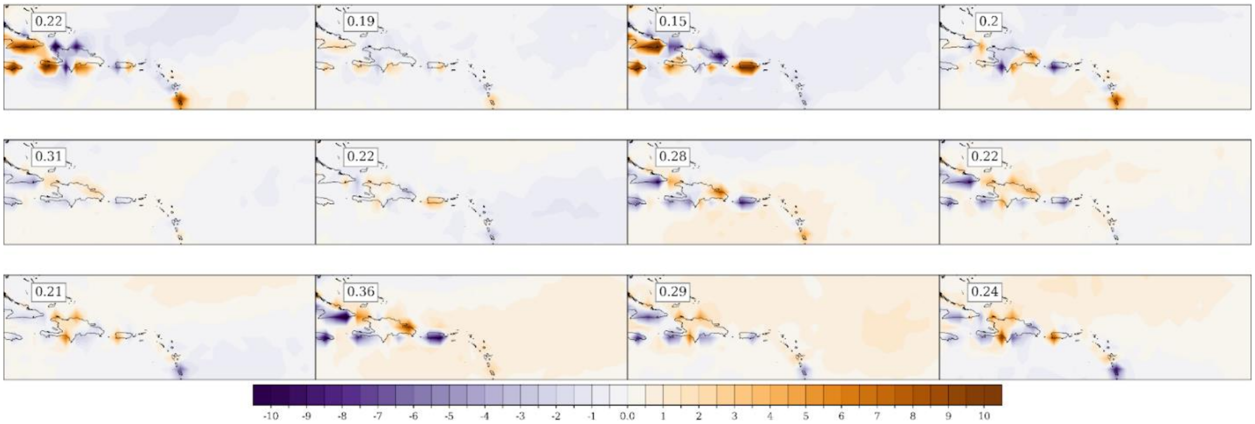


Figure 4.12: 5-Day Mean Vertical Velocity Anomalies (Pa s^{-1}*2) at 700 (top), 850 (middle), and 1000 (bottom) hPa for a 12-node SOM.

Vertical velocity anomalies can tell a lot about the upward and downward movement of air, thus providing some information about instability and potential precipitation or lack thereof. While there is some noise in the 1000 hPa plots due to the land masses, much more interesting anomalies are at play with vertical velocity anomalies. The 850 hPa shows a clear pattern: higher flash drought percentage is associated with positive anomalies ahead of Puerto Rico (first three nodes), while lower flash drought percentage is associated with negative anomalies ahead of Puerto Rico (last three nodes). In these figures, positive vertical velocity anomalies (orange) indicate atmospheric subsidence, which is the downward movement of air parcels. Downward movement can be associated with high pressure, lack of precipitation, and drought. The Ford & Labosier, 2017 study found that flash drought in the United States was partially exacerbated by a persistent ridging pattern in the mid latitudes, which caused high pressure environments that aid drought's persistence. Much in the same way as the 850 hPa map, the 700 hPa map shows similar atmospheric patterns and flash drought percentages. Inversely, the negative vertical velocity anomalies (purple) indicate potential atmospheric convection and lifting of air, which are excellent conditions for precipitation and recharging of soil moisture. These patterns are consistently shown to have lower flash drought percentages, which could be explained by these patterns providing rainfall to recharge the soil moisture deficit in many cases.

4.3.4 Zonal and Meridional Winds

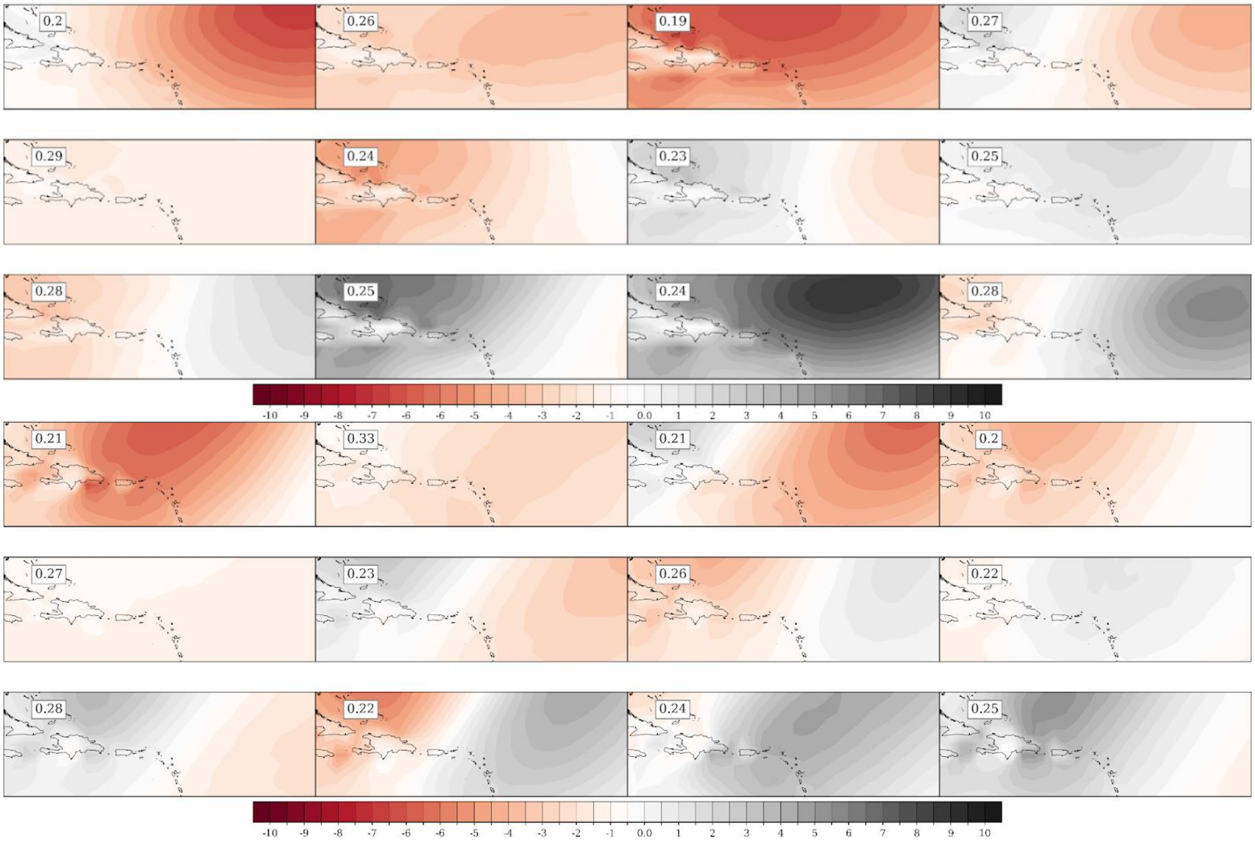


Figure 4.13: 5-Day Mean U (top) and V (bottom) Anomalies (m s^{-1} *0.02) at 1000 hPa for a 12-node SOM.

Like the temperature plots, the wind SOMs are not providing much explanatory value for flash droughts, as shown by similar flash drought day frequencies spread amongst all the nodes. The one general pattern that could be meaningful is that in both the zonal and meridional wind components, the weaker the gradient, the higher the flash drought percentages. While the percentages are fairly uniform, note that node five for the zonal wind and node two for the meridional wind contain the highest percentage for their respective SOMs, and they both have a fairly uniform wind compared to the contours of the other nodes. Lack of strong winds could allow for persistence of patterns of subsidence, dust, etc. that could contribute to higher risk for flash drought.

4.3.5 Specific Humidity Anomalies

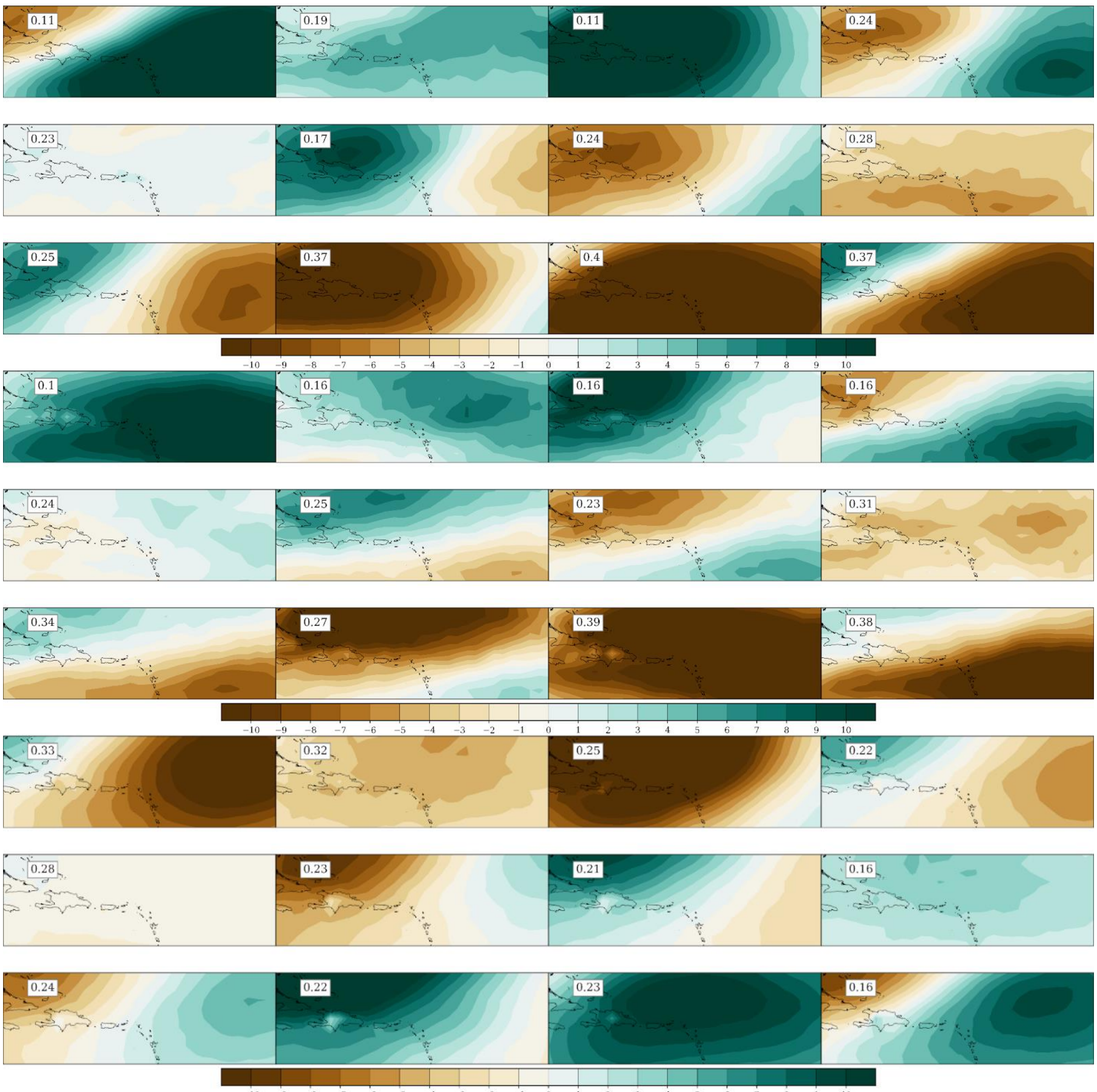


Figure 4.14: 5-Day Mean Specific Humidity Anomalies (kg kg^{-1} *100) at 700 (top), 850 (middle), and 1000 (bottom) hPa for a 12-node SOM.

Like the vertical velocity anomalies, these specific humidity SOMs exhibit extreme patterns that closely relate to the flash drought metric. The negative anomalies, or driest conditions, ahead of Puerto Rico strongly associate with higher percent flash drought while the positive anomalies, or wettest conditions, strongly associate with lower percent flash drought. The most telling patterns are shown in node one of the 850 hPa map where only 0.1 of the flash droughts map to the extremely anomalous wet conditions, while node eleven shows the opposite with 0.39 mapping with extremely anomalous dry conditions. The simplest conventional knowledge of drought involves a moisture deficit as being the primary definition of drought. Whether that moisture is evaporated or simply not present at the start, drought is shown here to be more frequent without moisture. These patterns show this convention extremely well, and further indicate the need to better understand how these moisture anomalies are being created, which aids in prediction of flash drought events.

4.3.6 Saharan Dust

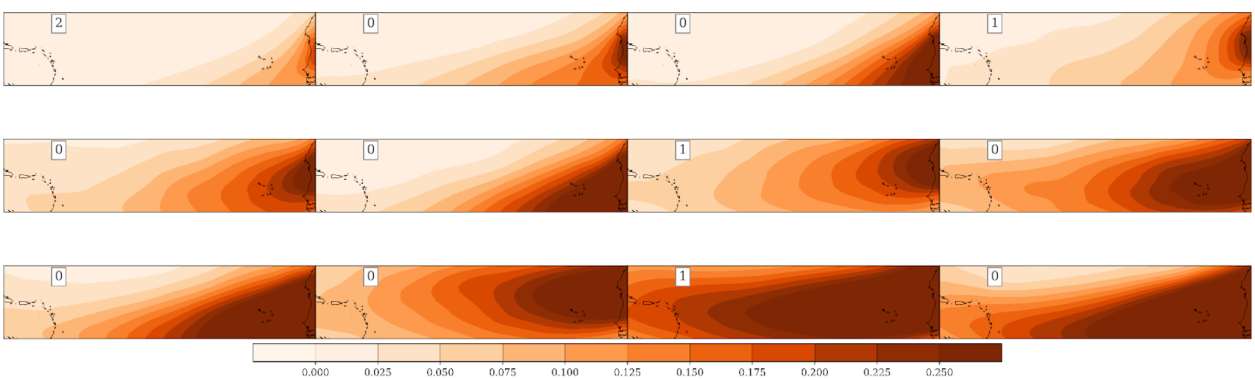


Figure 4.15: 5-Day Mean Dust Aerosol Depth at 550 nm for a 12-node SOM.

The Saharan dust transport is assessed using dust aerosol data with an optical depth at 550 nm. These data are dimensionless and integrated through the troposphere. Like the ERA5 data, these data are produced by EAC4 (ECMWF Atmospheric Composition Reanalysis 4). The number in the top left corner corresponds to the number of flash drought events within that node. Note two events in node 1 where there is very little dust, and 1 event in node 11, where there is a significant mode of transport directly from Africa to Puerto Rico. Unlike the many of the SOMs in this section, this SOM used EDDI as the flash drought definition. The EAC4 dust data only goes back to 2003, so the temporal scale is smaller overall. Further, the dust is not significant every day, unlike normal atmospheric variables. To properly analyze the dust, filtering of the data to the dust season would be necessary, which further shortens the temporal scale. The U.S. Caribbean dust season often extends from the end of the dry season (e.g. March) through the early rainfall season (e.g. July; Mote et al. 2017). Overall, this SOM shows some interesting modes of variability with dust transport, but because of the smaller temporal scale, it would need to be assessed in future work to see how closely dust affects flash drought in Puerto Rico.

4.4 Nested SOM

A nested SOM takes the data from a singular node in a parent SOM (i.e. trained on the entire 40-year climatology) and creates a new SOM based on that singular node to analyze the variability from within a node of the "parent" SOM. The benefit of this technique is to find more specific patterns (i.e. more extreme) from the most interesting observations in the original SOMs. Given the 5-day running mean SOMs above, the most telling atmospheric patterns included the 850 hPa vertical velocity and 850 hPa specific humidity SOMs. Increased subsidence and dry moisture anomalies seemed to be the most associated with flash drought events from the analysis presented in sections 4.2 to 4.3, so nodes from these SOMs were used to run nested SOMs to see how these patterns break down even further. The primary goal of the nested SOM is to see if there are any distinct patterns within nodes of interest that can be identified as a significant driver of flash drought.

4.4.1 Vertical Velocity

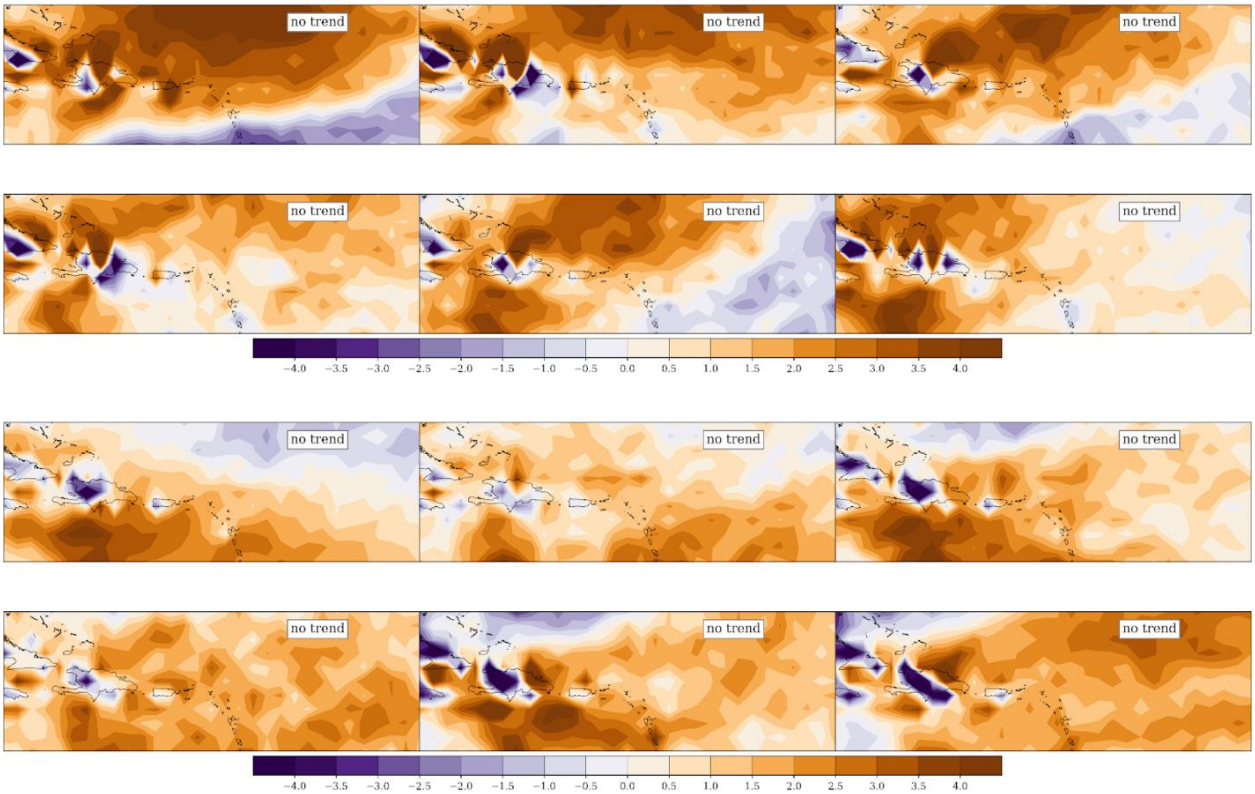


Figure 4.16: 5-Day Mean Vertical Velocity Anomalies (Pa s^{-1}*100) from Nodes 1 (top) and 3 (bottom) of 850 hPa SOM shown in Figure 4.12.

While subsidence was expected in these nodes, the goal was to see how these subsidence patterns broke down. The first node within node one's SOM (top) shows some of the most intense gradient of vertical velocity ahead of Puerto Rico among all SOMs while node six shows intense subsidence west of Puerto Rico. Node three's patterns are a little less extreme; however, the main node of interest is the third node within node three where there is a significant amount of subsidence approaching Hispaniola, where a lot of upward vertical motion is occurring. Unfortunately, this region seems to show some noise within the nested SOM, so to get a better understanding of how these patterns are created, we shrink the domain to exclude Hispaniola.

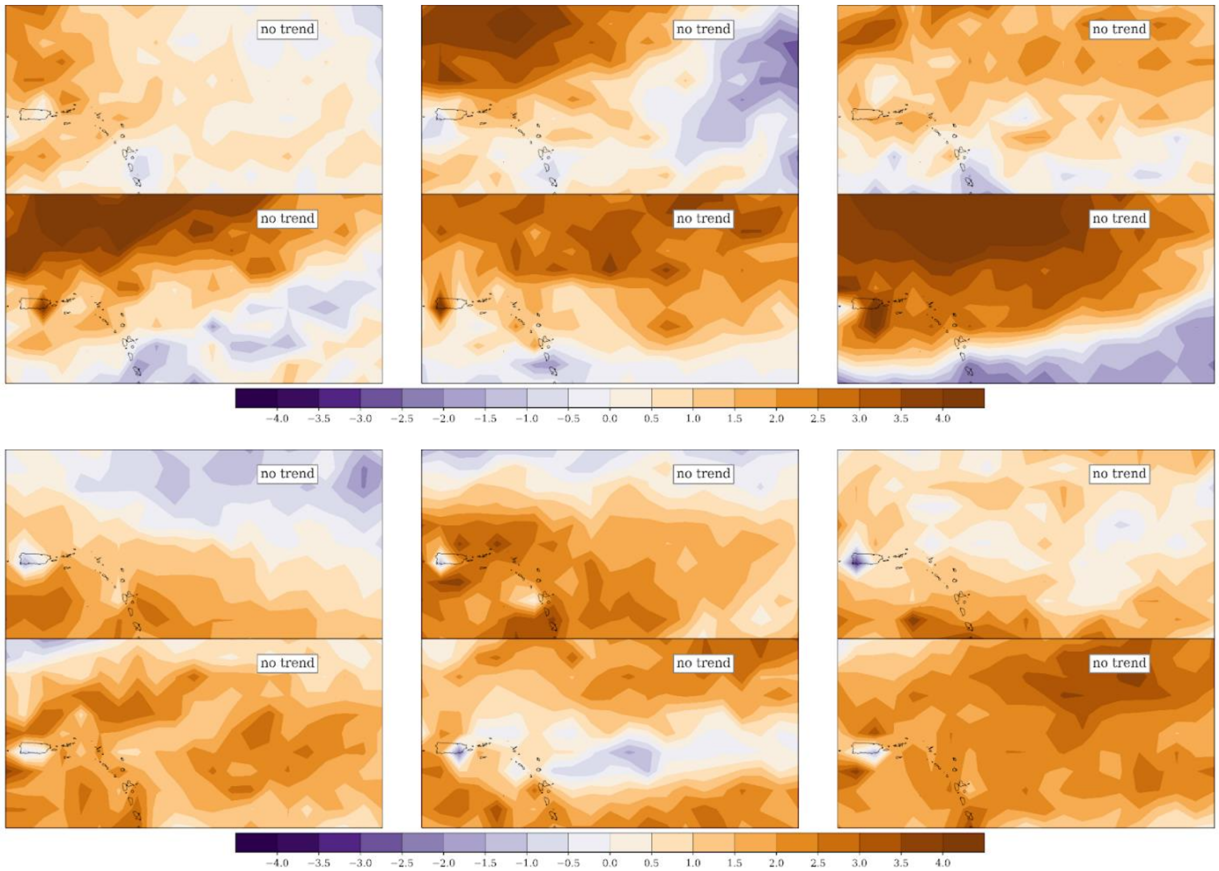


Figure 4.17: 5-Day Mean Vertical Velocity Anomalies (Pa s^{-1} *100) from Nodes 1 (top) and 3 (bottom) of 850 hPa SOM shown in Figure 4.12 without the Hispaniola region due to noise.

In node one’s nested SOM, node six shows an extreme vertical motion gradient with subsidence north and east of Puerto Rico and a mass of lifting air south of that mass. While this pattern did not show a significant trend of increasing or decreasing, it can be seen how rather than a particular node of extreme subsidence contributing to this SOM, it is rather any patterns that include a mass of subsidence overall. This result suggests that persistent subsidence ahead of Puerto Rico can contribute to flash drought days for the island.

4.4.2 Specific Humidity

Like the vertical velocity nested SOMs, the goal here is to better understand how these dry air masses are contributing to flash drought in more detail.

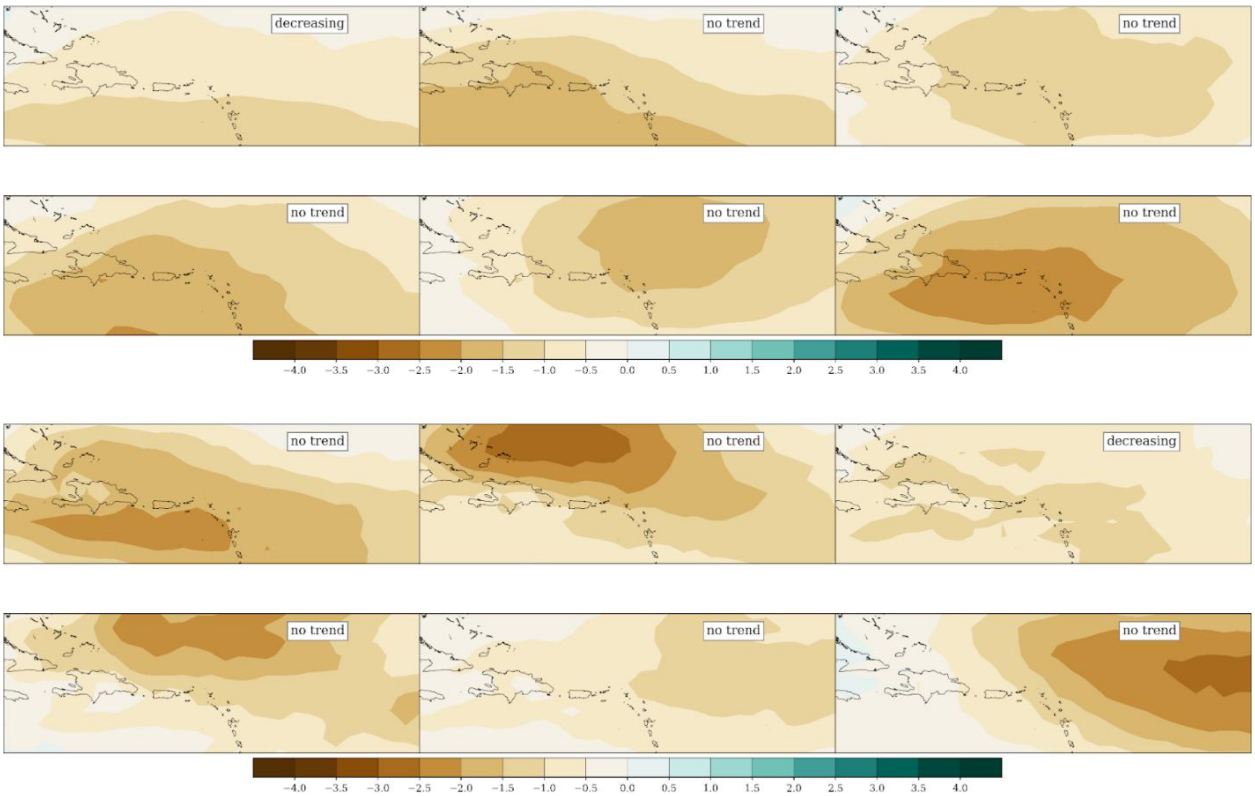


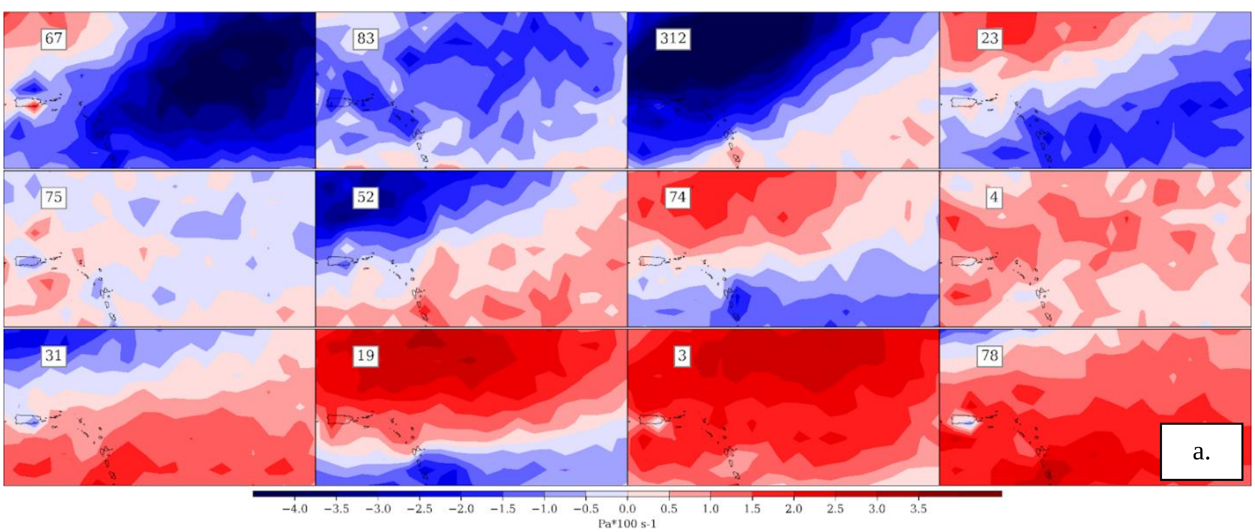
Figure 4.18: 5-Day Mean Specific Humidity Anomalies (kg kg^{-1} *1000) from Node 11 shown in Figure 4.15 of 700 (top) and 850 (bottom) hPa SOM.

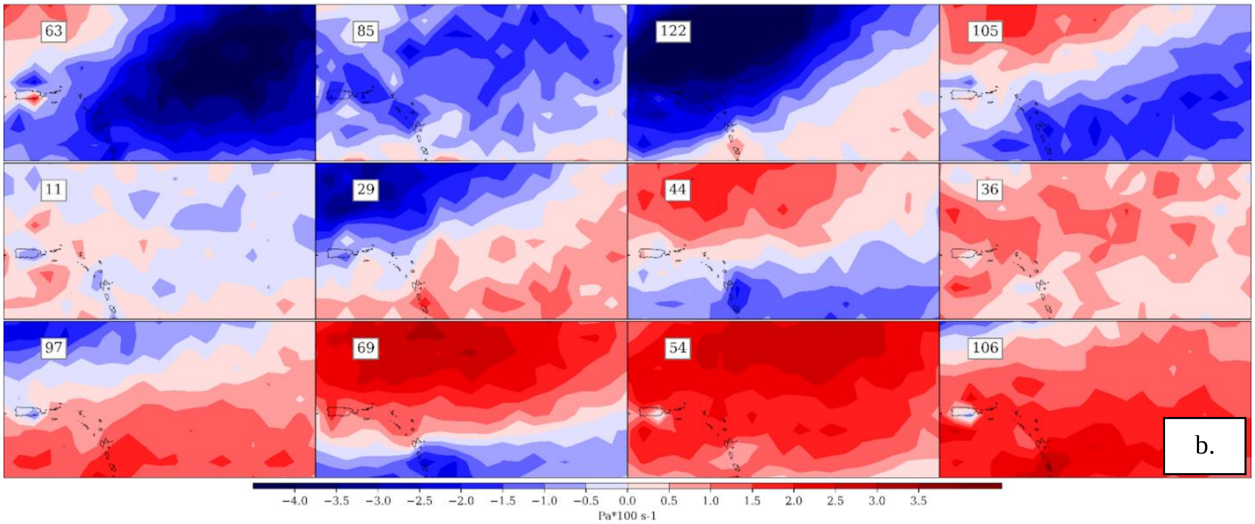
Unsurprisingly, these SOMs show extremely dry anomalies throughout, and the patterns of these dry anomalies can say something about how these air masses move across this region. Node six within the 850 hPa node eleven SOM shows a more elongated gradient of dry air, which could potentially be associated with the Saharan Air Layer given its geographic pattern coming off the coast of Africa by the easterly trade winds. Future research should be conducted on how the Saharan Air Layer may influence these dry moisture anomalies.

4.5 Evaporative Demand Drought Index derived Flash Drought SOMs

While most of the previous SOMs incorporated the soil moisture definition for flash drought using the GLDAS soil moisture definition, the following results incorporate the EDDI definition. This version of flash drought provides near real time information on the emergence or persistence of anomalous evaporative demand in Puerto Rico (Physical Science Laboratory, 2022). This definition will allow for a specific analysis on determining the atmospheric conditions forcing flash drought initiation and is determined by the robust EDDI definition, which is calculated using temperature, specific humidity, winds, and solar radiation. EDDI was specifically designed to be an early flash drought detection index, as it is highly sensitive to atmospheric demand for evaporation (Hobbins et al., 2016). Often, EDDI has been shown to start to increase before soil moisture deficits are detected (Hobbins et al., 2016).

4.5.1 Vertical Velocity Anomalies




63
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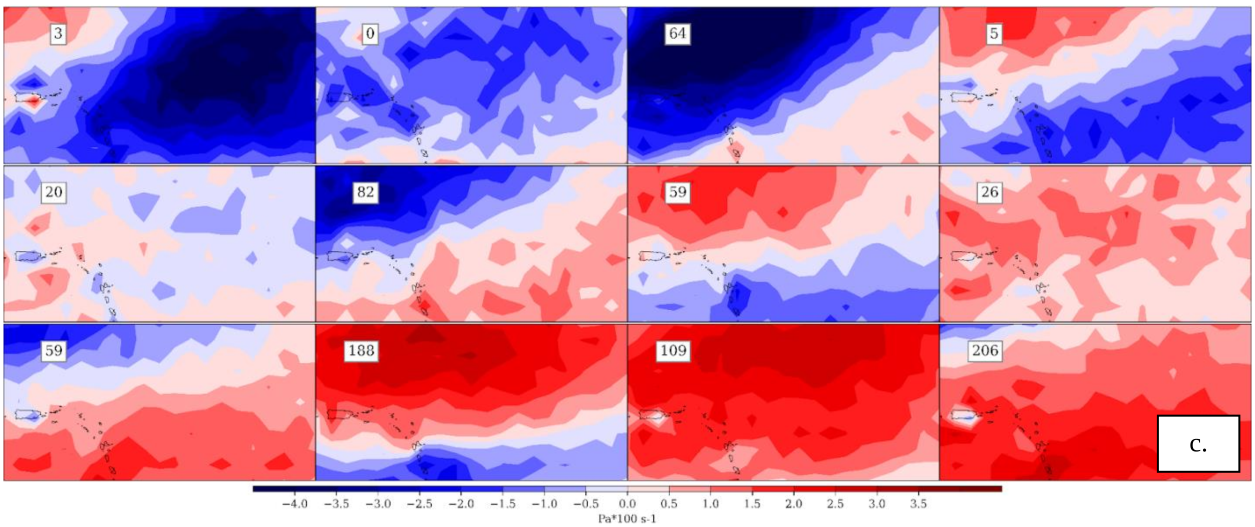
Pa*100 s-1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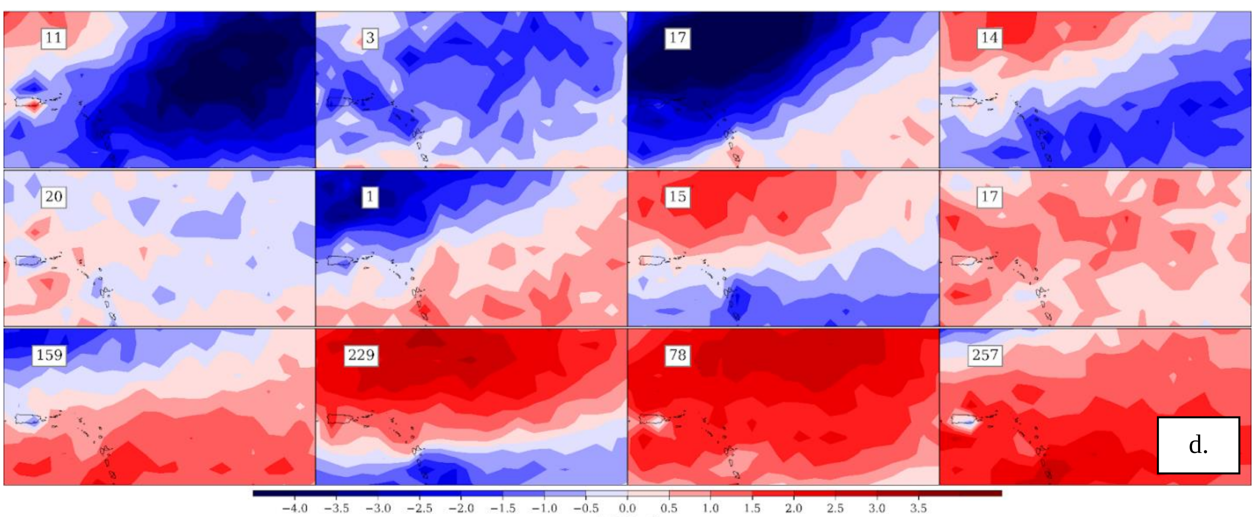
Pa*100 s-1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Pa*100 s-1

Figure 4.19: 5-Day Mean Vertical Velocity Anomalies at 850 hPa with EDDI calculated to show flash drought days in each node at day 0 (a.), day 5 (b.), day 10 (c.), and day 15 (d.).

EDDI can be combined with SOMs to better understand how flash drought is associated with certain atmospheric conditions. For Figure 4.19, the EDDI flash drought metric on the entire 40-year climatology for the island of Puerto Rico was calculated and all flash droughts were identified. In Figure 4.19a, the text displayed in the upper-left hand corner displays the number of pentads (e.g. five-day periods) where flash drought initiated. In Figure 4.19b, the upper-left hand corner shows the number of flash droughts that initiated in the previous pentad. In Figure 4.19c, the upper-left hand corner shows the number of flash droughts 10-15 days after drought initiation. Lastly, Figure 4.19d shows the conditions on days 15-20 of the flash drought.

Since discovering vertical velocity seems to be associated with flash drought, the first attempt to use EDDI was using vertical velocity to see how this matched up with the soil moisture definition. At day zero, node three shows an overwhelming amount of flash drought day compared to the other nodes, which is the node with an anomalously high amount of upward vertical motion (blue). In the following two images where five and ten days are passed respectively, a transition is evident between the SOM nodes before the fifteen-day image (Figure 4.19d). At ten to fifteen days (Figure 4.19c) after this anomaly of lifting air, the SOM shows persistent subsidence being associated with most flash drought days using the EDDI definition. Not only does this finding validate the discoveries made with the soil moisture deficit definition, but it also reinforces the concept that for flash drought to initiate and intensify, potential evaporation/evapotranspiration needs to be high to start, followed by a lack of precipitation, which in this case is inferred by persistent subsidence. Subsidence of this magnitude suggests that the atmosphere cannot get air to lift enough moisture for a precipitation event, so dryness persists after the high amount of evaporation demand, which would cause drought to rapidly intensify over the next two weeks after the initiation event, thus resulting in a flash drought event.

The full evolution of a flash drought event using EDDI begins with a rapid intensification of evaporative demand, and the continuation of that demand for approximately two weeks thereafter. Negative EDDI indicates wetness, so there is no "thirst" from the atmosphere while positive EDDI indicates dryness, thus a "thirst" to replenish wetness through increased evaporation. Flash drought therefore can, but does not have to, be shown from a negative to a positive anomaly in the 5-day lag time (Figure 4.20) if the increase is at least a 50% jump and is sustained over the next two weeks.

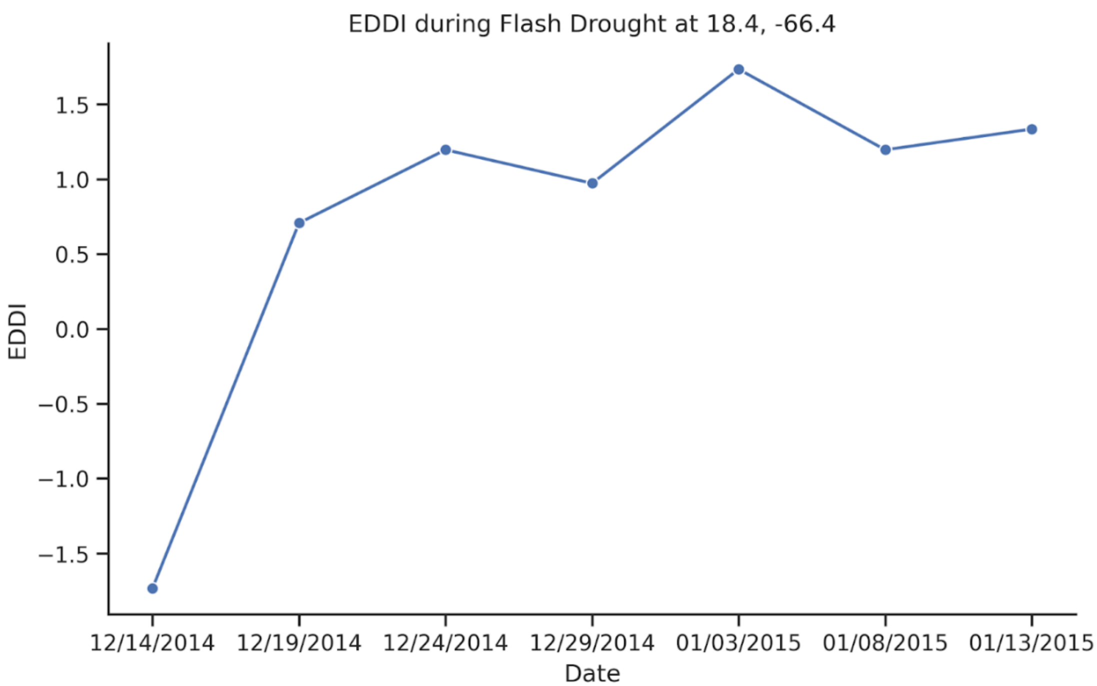
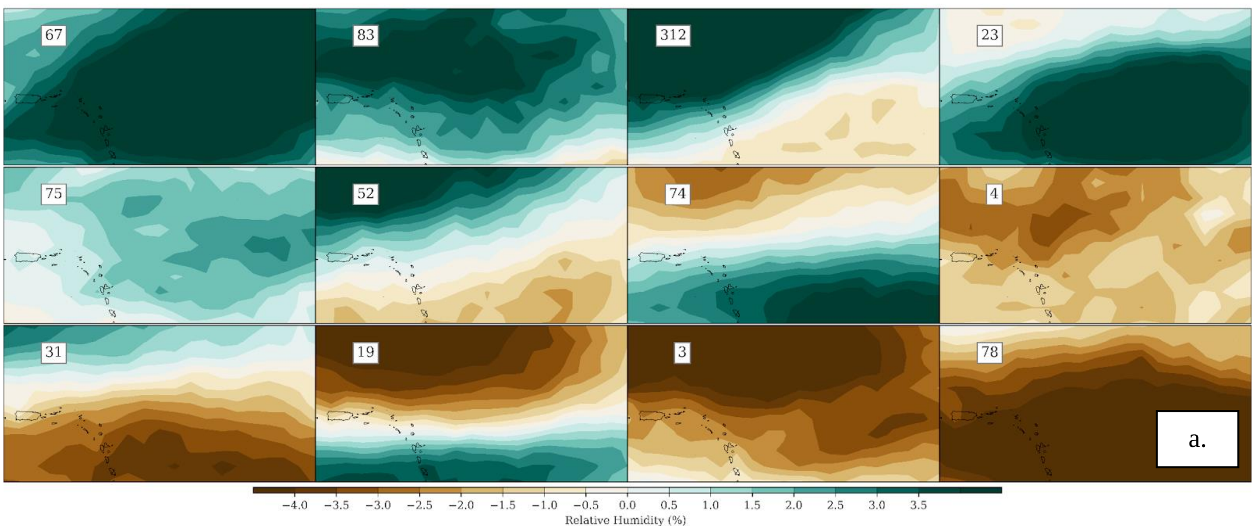
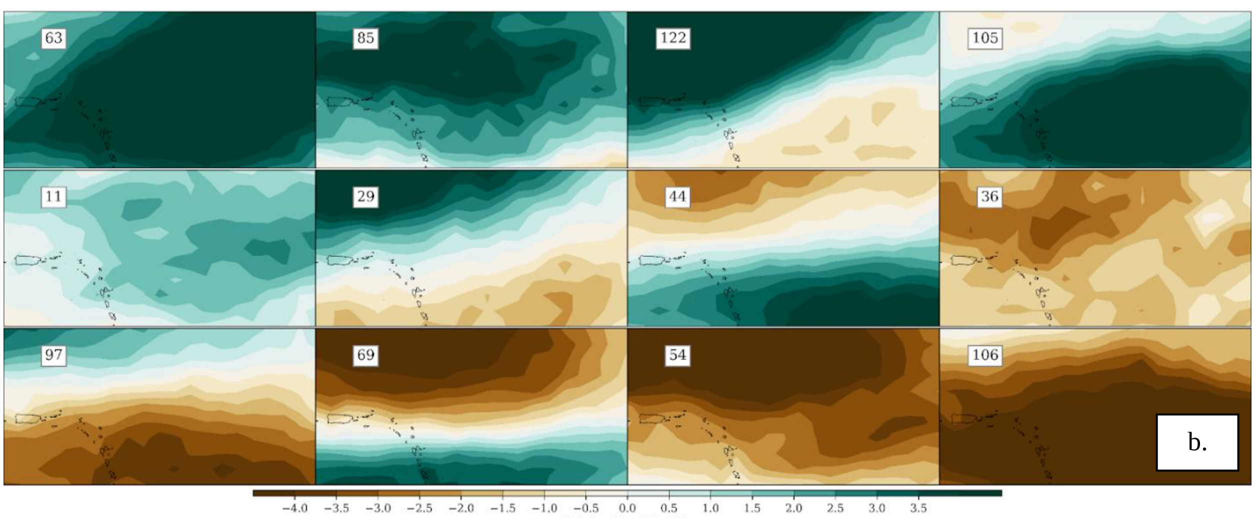


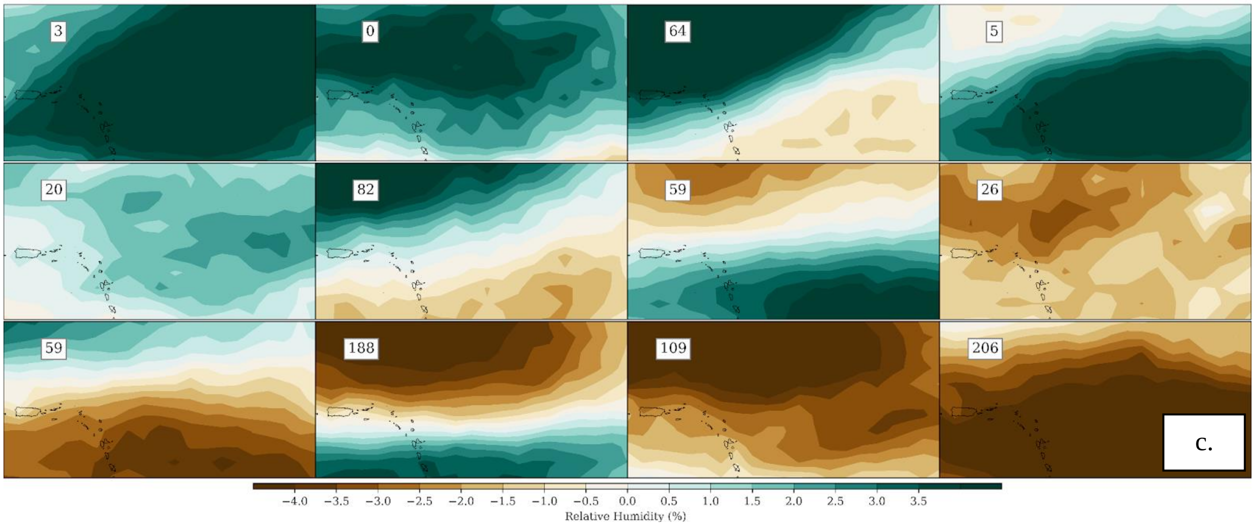
Figure 4.20: EDDI evolution for December 14, 2014, flash drought event.

Not only was the December 14, 2014, event well above the 50% increase in percentile of EDDI, the evaporative demand sustained over the next two weeks without dropping down to the previous levels. This evolution of a flash drought event matches the pattern shown with the vertical velocity patterns (Figure 4.19). An anomalous increase in upward vertical motion corresponds well to the period right before the rapid increase in evaporative demand. Once the increased vertical motion dissipates, subsidence persists, corresponding to the "leveled off" period of the evaporative demand. The atmosphere has this intense thirst for moisture, but due to the persistent subsidence, flash drought can propagate. An extremely similar pattern is shown when analyzing relative humidity in the same way. The event shown in Figure 4.20 likely represents the initiation of not only a strong flash drought, but also the initiation of the long-term 2015 drought discussed in previous literature (Mote et al. 2017).

4.5.2 Relative Humidity Anomalies



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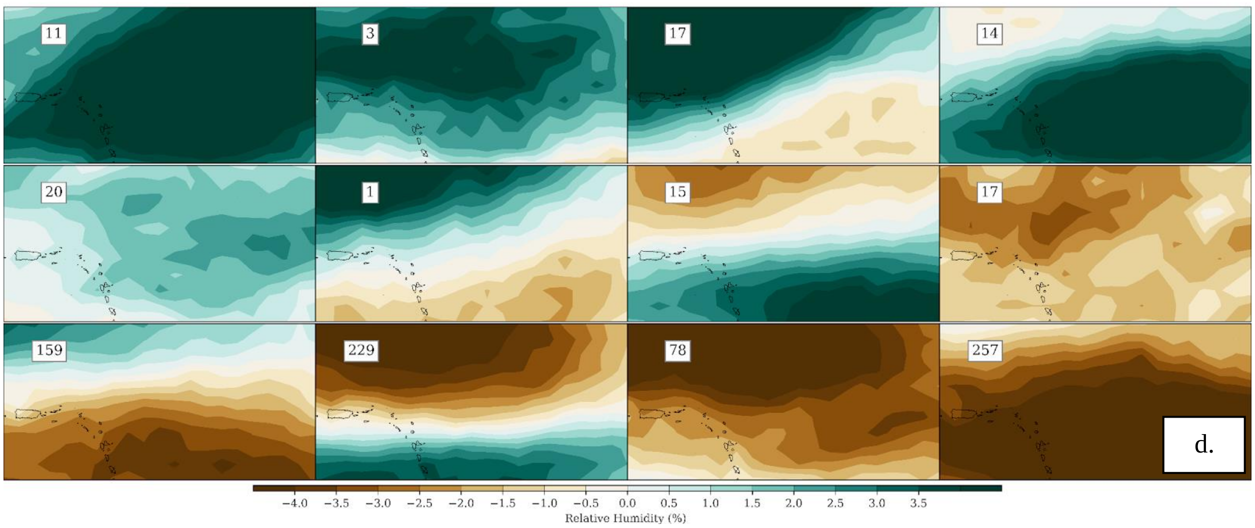
Relative Humidity (%)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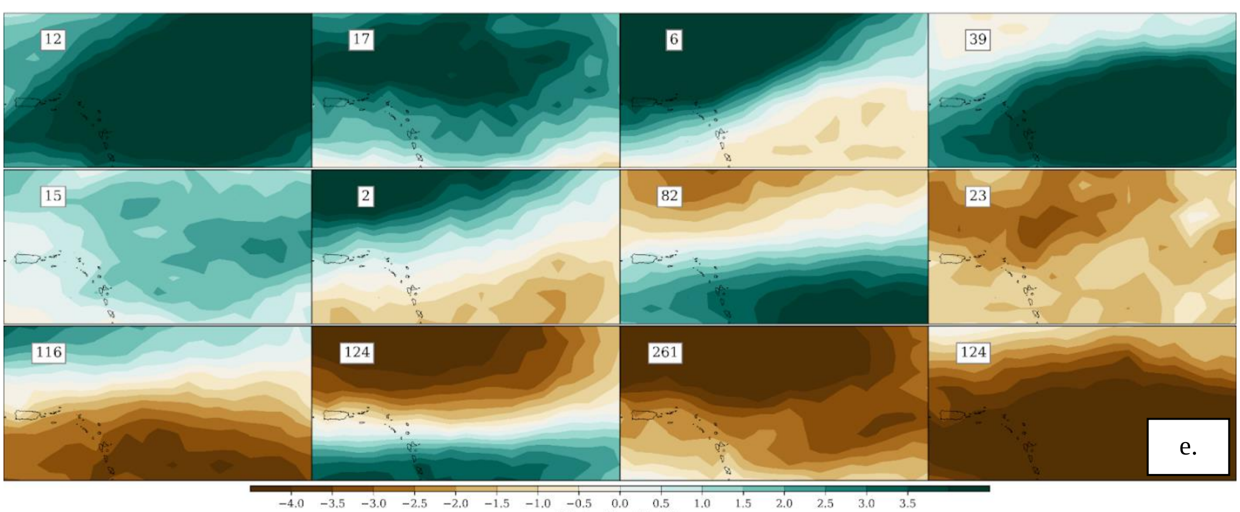
−4.0 −3.5 −3.0 −2.5 −2.0 −1.5 −1.0 −0.5 0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5
Relative Humidity (%)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e.
−4.0 −3.5 −3.0 −2.5 −2.0 −1.5 −1.0 −0.5 0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5
Relative Humidity (%)

Figure 4.21: 5-Day Mean Relative Humidity Anomalies at 850 hPa with EDDI calculated to show flash drought days in each node at day 0 (a.), day 5 (b.), day 10 (c.), day 15 (d.), and day 20 (e.).

Analyzing the relative humidity anomalies associated with EDDI defined flash drought reinforce the relationship between subsidence and atmospheric humidity in this context. Figure 4.21 takes the results of the SOM for the vertical velocity discussed in Section 4.5.1 and analyzes the relative humidity for the SOM. While the vertical velocity anomalies show persistent subsidence implying dryness, Figure 4.21 shows how the atmospheric moisture responds with EDDI. Note in Figure 4.21a over 300 flash drought events initiated during anomalously wet atmospheric conditions. The following days slowly show the amount of flash droughts associated with drier and drier atmospheric conditions until 20 days after initiation where most flash drought events are associated with extremely dry conditions. This pattern directly corresponds with the discoveries made with the vertical velocity anomalies, which also reinforces well understood atmospheric science dynamics. Subsidence induces adiabatic warming in the low troposphere which decreases relative humidity.

4.5.3 EDDI Flash Drought Events

After using EDDI with the vertical velocity and relative humidity SOMs, it is important to understand how the flash drought events affected Puerto Rico according to EDDI. This definition can help to understand the initiation of flash drought, and by using the grid points over Puerto Rico, it can be discovered how widespread the flash drought event is over the island.

Years	Months	Days
1983	11	4
1991	7	17
1997	10	10
2002	2	27
2002	4	23
2003	4	18
2010	3	9
2010	11	9
2012	8	26
2014	12	14
2015	7	12
2015	11	29

Table 4.1: Large flash drought events (>20 grid points in Puerto Rico) using EDDI definition.

This table shows the larger flash drought events (greater than 20 grid points that initiated flash drought during the same pentad) over the island based on the available data and the EDDI definition. The most intense flash droughts according to the soil moisture definition (only dating back to 2000) occurred in 2002 to 2003 and 2014 to 2015. The EDDI definition found a few flash drought initiations in 2002 and 2003 suggesting that these periods of rapid intensification may have contributed to the soil moisture deficit seen previously, which prolonged a drought that may have already been initiating more slowly. Additionally, one of the major implications found here is the December 14, 2014 flash drought initiation, which lines up extremely well with the intense flash drought event studied in Mote et al., 2017 that contributed to the creation of this research. Further research will be done to see how this initiation period was able to onset such a drastic event. Lastly, this table uses data dating back to 1979, so it is certainly of interest that of the twelve initiation periods, 50% occurred in 2010 to 2020, and 75% occurred from 2000 to 2020, suggesting that the conditions for flash drought initiation in Puerto Rico are intensifying in the past twenty years.

Chapter 5: Conclusion and Future Work

Drought has always and will continue to cause major agricultural, financial, and societal problems for humans. In order to manage these situations, humans have to innovate solutions to mitigate and adapt to the drastic effects of drought, especially the less well-known flash drought. Flash drought's rapid onset and intensity is not well researched; therefore, prediction and adaptation to these events are extremely difficult. This research takes a major first step in understanding the antecedent and concurrent atmospheric conditions associated with flash drought in Puerto Rico, which has been extremely understudied. Rather than using the USDM, this research incorporates two definitions of flash drought from the literature: one based on soil moisture deficit, and one based on EDDI, a novel drought monitoring metric. Using these definitions along with the power of self-organizing maps, this research found some interesting conclusions:

- Subsidence, especially in the 700 to 850 hPa range, upwind of Puerto Rico tends to be associated with flash drought initiation.
- Negative specific humidity anomalies tend to be associated with flash drought maintenance as well.
- While the soil moisture deficit definition provides meaningful results, the EDDI flash drought definition is a promising way to monitor flash drought in the Tropics. While EDDI is helpful for measuring all modes of drought, it appears to perform particularly well at determining flash drought initiation.
- When analyzing vertical velocity using the EDDI flash drought definition, there is evidence that an anomalous upward vertical velocity event, followed by persistent subsidence throughout the next 15-30 days, is a primary driver of flash drought in Puerto Rico.

- Relative humidity anomalies reinforce the relationship between vertical velocity and atmospheric moisture and indicate that persistent subsidence is associated with atmospheric dryness and propagation of flash drought.
- Most large flash drought events have occurred over the past twenty years dating back to 1979, suggesting these events are only becoming more frequent and potentially more intense (see 2015 event) in the future.

Future work will address numerous research questions that arose during this study. The Bermuda High atmospheric pattern will be closely analyzed for its association with variations in flash drought. Other teleconnections like the El Niño Southern Oscillation (ENSO) and Madden–Julian Oscillation (MJO) may be analyzed as well because of their association with tropical atmospheric patterns. Saharan dust anomalies will be analyzed for a closer association with flash drought specifically, especially the seasonality of flash drought and how the Saharan Air Layer may play a role. Some of the limitations in this work include the data resolution. While the highest resolution data available was used, the small study area of Puerto Rico and the temporal scale of the GLDAS data being 20 years could ideally be improved. Future work can incorporate any new land reanalysis datasets that are produced. Lastly, additional SOMs with more node types of vertical velocity and specific humidity, as well as SOMs of atmospheric variables at 500 hPa could improve this study.

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