Rain, Rain, Go Away:

Historic Rainfall Analysis in the Baltimore Region

by

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Department of Civil and Environmental Engineering

Princeton University

Declaration of Authorship

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Abstract

In July of 2016 a devastating 3-hour rainstorm with a predicted return interval of 1000 years struck Ellicott City, Maryland. In May of 2018, a 3-hour rainstorm with the same predicted 1000 year return interval struck Ellicott City **again**. These anomalous events bring into question whether methods assuming stationary climate are accurate and if precipitation or storm intensity is increasing as a result of climate change. The Ellicott City storms are assessed using basin-averaged precipitation over the entire Baltimore Region and evaluated by creating a high resolution 20-year dataset. These analyses allow for high spatial and temporal resolution to be focused on a small region. Single Polarimetric Radar and Dual Polarimetric Radar data are also used to create a 20-year high resolution rainfall dataset. I conclude that there is not strong evidence for increasing frequency in precipitation for the mid-Atlantic region encompassing Ellicott City. Assessing fluctuating frequency of extreme precipitation is notoriously difficult but using this 20-year novel data set provides insight into how potential hazards can be addressed in the warming climate. Precipitation changes are additionally put into context with the 2020 pandemic and its ramifications for economic sector change and energy policy. Methodologies created here can be applied to other high-resolution rainfall datasets to assess non-stationarity within other regions, providing further insight into small urban watersheds.

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Chapter 1: Introduction

Increasing anomalous extreme precipitation patterns have brought into question how climate change has affected our world and what precautions we can take to mitigate the adverse consequences of it. Although increasing precipitation may only seem relevant in disaster scenarios, understanding its frequency and magnitude has many other applications. Whether it's snowpack in the Sierra Nevada Mountains or available cropping systems in the Pacific Northwest, understanding extreme rainfall and the effects of its increasing frequency will impact both your winter vacation activities and the food you eat.

An extreme rainfall event is defined as occurring when, "precipitation over some specified time period exceeds some threshold, either at a point (i.e., as measured by a single rain gauge) or in an average over some spatial region," and can vary widely by length or region of the storm [13]. Extreme drought, extreme heat and extreme cold are all weather events that are easily linked and highly researched as a result of climate change and increasing global temperatures [13]. However, extreme precipitation and the associated flash flood events are not as easily researched due to the varying magnitudes of storm classifications by spatial region, storm length, and data availability.

1.1 Motivation

An area that is largely unexplored within precipitation and flash flood events is small urban watersheds, populated areas that are basins bounded by topographic features [14]. These small urban watersheds are more likely to be devastated by a flash flood event due to their drainage basin size. Urban planners are additionally concerned about the infrastructure's ability to withstand the extreme conditions anticipated in the next 20 to 50 years.

Figure 1.
Ellicott City Main Street July 2016

Figure 2.
Ellicott City Main Street May 2018

Ellicott City, Maryland is a town of 71,000 people located just west of Baltimore [15]. It was devastated in 2016 with an extreme precipitation event and flash flood leading to fatalities and massive destruction (Figure 1). An extreme precipitation event of any magnitude exceeding this storm had a 1 in 1000-year return interval (Figure 3) [16]. But against all odds, Ellicott City was overwhelmed with another storm given the same return interval in May 2018, just 22 months later (Figure 2). The temporal proximity of these catastrophic events brings into question not only if the methods used to calculate the storm return interval rate are accurate, but how to deal with a potential for increasing frequency and magnitude of these extreme events.

"So, we have questions. Is this really a once in a thousand-year event? Obviously, it was not for our generation. What are the causes, and how can we mitigate it? Is it development? Is development the main culprit here, when we look at increased population and more concrete rather than allowing runoff to occur in a more natural way? What impact is climate change having on what we are doing?"

— *U.S. Senator Cardin, State of Maryland* [27]

In August 2018, a hearing was held to discuss the government's role to prevent flooding in Ellicott City. Senator Benjamin Cardin mentions some key points that need to be addressed regarding extreme precipitation: what are the causes, how can we mitigate them, and are the methods currently being used accurate? This last question brings up an important motivation for assessing frequency and magnitude over time for extreme precipitation, as NOAA had not accounted for non-stationary climate in their prior studies.

"The current approach used in NOAA Atlas 14 to calculate precipitation magnitude-frequency relationships assumes stationarity in the annual maximum series (AMS) data used for frequency distribution selection and fitting… However, it is questionable if use of stationary methods relying on AMS data is appropriate for the analysis of extreme precipitation in the presence of nonstationary climate."

— *Office of Water Prediction, NOAA* [17]

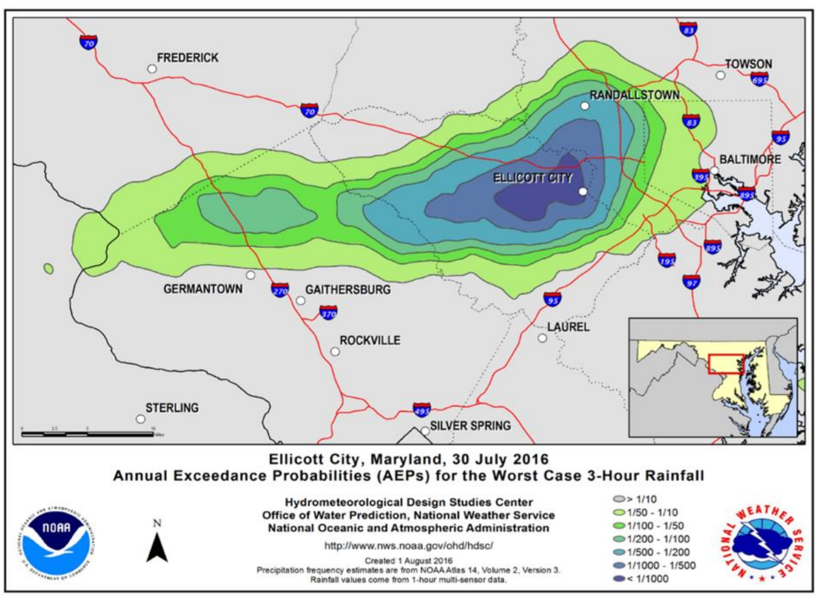

Figure 3.
NOAA Exceedance Probability July 2016

In January 2018, NOAA stated in their quarterly report that the current assumption of stationary climate would not work in non-stationary climate and that steps would be taken to assess how to account for this [17]. NOAA's storm return interval rate (Figure 3) demonstrates the outcome of using historic data to find annual exceedance probabilities. This Atlas 14 stationary strategy is again used for the May 2018 Ellicott City storm (Figure 4) to calculate the annual exceedance probability of yet another extremely rare precipitation occurrence.

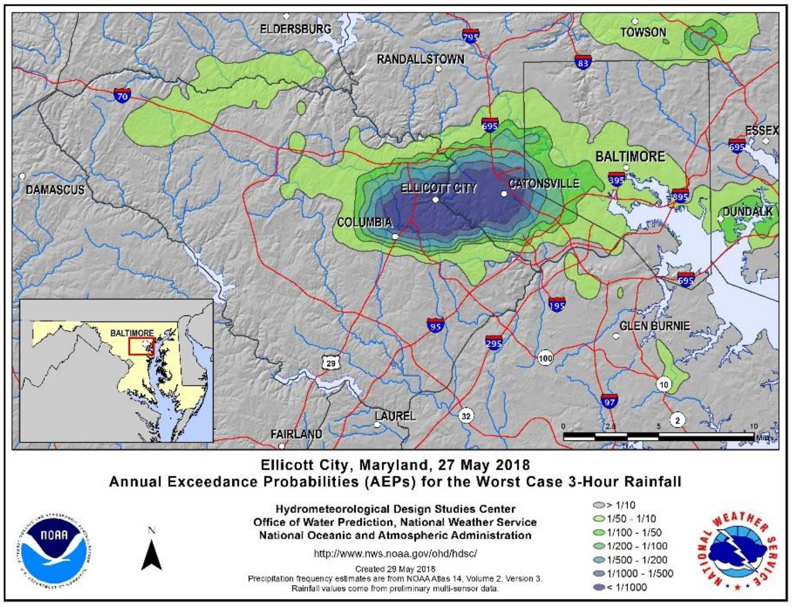

Figure 4.
NOAA Exceedance Probability May 2018

Senator Cardin's questions and NOAAs questioning of their own methods motivates my research into nonstationary climate modeling within small scale urban watersheds. The last significant analysis done within the Baltimore Region was in 2015 which was prior to the unprecedented 2016 and 2018 extreme precipitation events in Ellicott City. The 2016 and 2018 storm events were documented by Dual Polarimetric Radar (Dual-Pol), the latest precipitation technology, and will help to analyze a small-scale area with very fine spatial resolution. In addition to these datasets, a year to year rain rate dataset was put together in December 2019 using both Single Polarimetric Radar (Single-Pol) and Dual-Pol measurements for the Baltimore Region. Compiling this dataset together to seam the Single-Pol and Dual-Pol measurements will provide a coherent story into how extreme precipitation has changed throughout the decades. This dataset has fine spatial resolution with rain rates recorded every 15 minutes which will bring new insight into magnitude and frequency trends of precipitation.

1.2 Objectives

The aim of this research is to integrate the available data from the Baltimore Region to further understand small urban watersheds and how to assess the negative impacts of extreme precipitation events in this and other small urban watersheds. This will also be a search for clues of non-stationary climate and a look into how this could affect energy policy in the future.

The first objective is to use the 2016 and 2018 Dual-Pol data for Ellicott City, MD to understand the basin flows into the watershed as well as to analyze storm similarities. The current understanding of the 2016 and 2018 storms are based on sweeping conclusions founded in qualitative data and hearsay. Bringing in the rain rate data can shed light on how a storm of this magnitude occurred and which region contributed the most precipitation.

The scope of research will expand by analyzing a 20-year dataset spanning 2000-2019 for the Baltimore region and by stitching together the Single-Pol and Dual-Pol measurements over the decades to investigate if extreme precipitation events have increased in frequency or magnitude. This objective will additionally serve as a methods analysis by examining differences in measurements between Single-Pol and Dual-Pol as the datasets overlap. The last objective will be to provide an analysis for Ellicott City and the surrounding area to reduce their risk of flash floods as well as evaluate how energy policy and current sustainable energy practices will be impacted by extreme precipitation events and non-stationarity. The research and methodologies created for analyzing extreme precipitation can be used on other small urban watersheds with a high risk of flooding (such as Princeton, NJ) in addition to assessing for non-stationarity in new regions.

1.3 Research Questions

- How did precipitation for two 1000-year storms over Ellicott City vary in time and space?
- How does rainfall variability in time and space control catastrophic flood peak magnitudes in small urban watersheds?
- Have cloudburst storms increased in frequency or magnitude over the past several decades?

Chapter 2: Literature Review

2.1 Precipitation & Flash Flooding

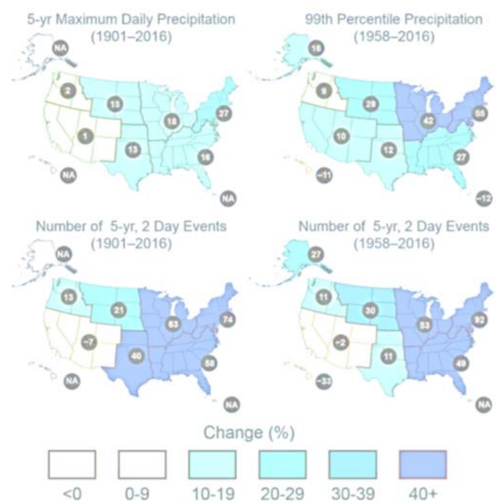

Figure 5.
5 Year Precipitation Events

Extreme precipitation has become more prevalent in the United States on both large and small scales. In a 2017 study focused on precipitation change across the United States it was found that the intensity and frequency of extreme precipitation events will continue to increase over the 21st century as they have been increasing since 1901 [4]. These projections indicate a 4% increase since 1901 with specific heavy precipitation increases over 5-year maximum daily precipitation by 27% in the Northeast [4]. A 2019 study focused on using 30-year data across Japan, Europe and the US expects similar increases in precipitation frequency and intensity [18]. The 2017 study found that the western US is expecting large declines in snowpack as expected snow across the east and central US will decrease and fall instead as rain [4].

Global Climate Models for crop systems across the United States also expect precipitation increases. In the Pacific Northwest (PNW) it was found that precipitation would increase by 5.8% from 2040 – 2069 with significant increases in the spring and winter months [19]. This winter increase has been noted in other studies in the PNW [20] but the spring is additionally important to address with regards to the Baltimore Region. According to the NOAA Extreme Climates Index, there is an upward increase in 1-day precipitation events in the Northeast region during the spring season (April-September) as well as an increase in precipitation days above the historical average [5].

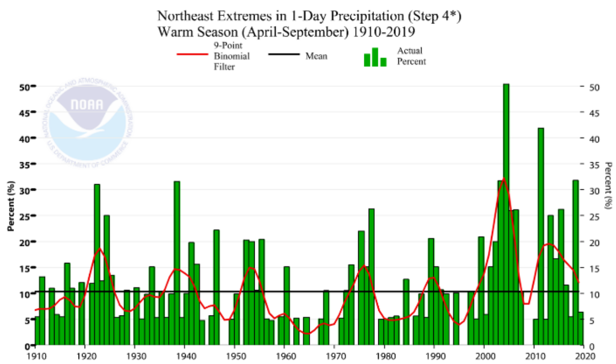

Figure 6.
1 Day Northeast Precipitation Extremes

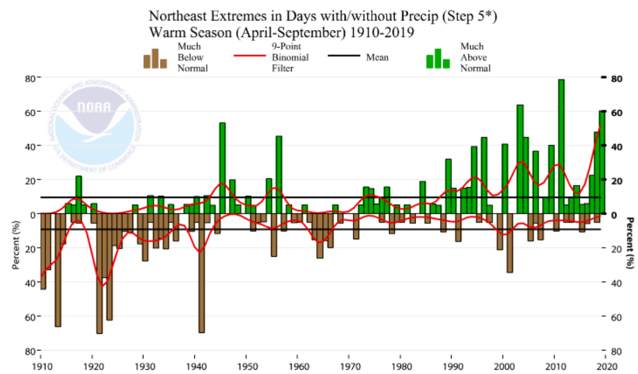

Figure 7.
Overall Northeast Precipitation Extremes (+/-

Since precipitation magnitude and frequency have been increasing since 1901 and are anticipated to keep on that upward trend, it follows that flash floods are becoming an important hazard to address.

"Flash floods are distinguished from 'normal flooding' by an abrupt onset arising from intense short period rainfall," a 2017 study focused on flash flooding within Britain states [21]. This study assessed historical information in attempts to understand how historical datasets can assist in projecting when rare flash flood events would occur [21]. The study found that historical records are useful mainly for finding frequency of flash flood events but that the potential for non-stationarity in historical data due to climactic variability and anthropogenic climate change impacts how predictions can be made for magnitudes of flash floods [21]. This demonstrates the difficulty in predicting flash flood events due to the potential storm length and magnitude which lowers confidence intervals for urban planners working within small catchments.

During potential disaster events the limited ability to predict flood magnitudes means that historical data is the only way to understand the largest factors that result in flash flood fatalities and mass destruction of urban areas. In a 2014 study, over 20,000 flash flood events were analyzed within the US from 2006–2012 to understand how to mitigate the human impacts from these destructive events [22]. This study found that flash flood impacts are magnified during short-duration events within small catchments and during times of reduced visibility [22]. Unfortunately for Ellicott City, its July 2016 and May 2018 extreme rainfall and flash floods fit these parameters, with rainfall occurring past dark (past 8 pm) and only lasting just over three hours.

2.2 Temperature Relations

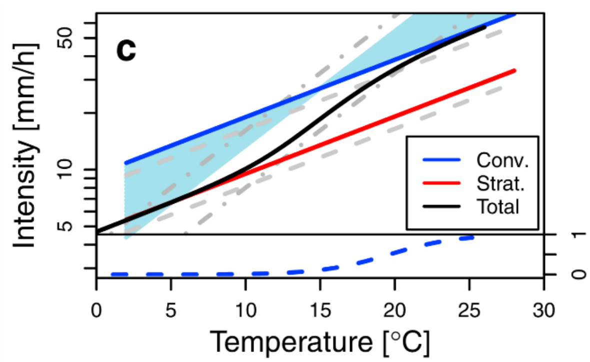

Figure 8.
Attribution of Storm Total to Convective

The links between climate change and precipitation increases are largely due to the dependence of precipitation on temperature, as temperature is a standard way for climatologists to indicate potential for climate change. The average rate of warming from the last 50 years is almost double that from the last 100 years, in line with global observed temperature rise [23]. "It is likely that the frequency of heavy precipitation events (or proportion of total rainfall from heavy falls) has increased over most areas… there is a wider consensus among models that global warming results in intensification of the water cycle, with more intense periods of rainfall and the lengthening of dry periods," [23].

Precipitation is related to temperature as it varies with the diurnal and seasonal cycles. Understanding these cycles is important as it pinpoints when precipitation should be at a maximum. The type of precipitation that is impacted by temperature rise is mainly convective precipitation. Convective precipitation has larger and varying drop sizes compared to stratiform precipitation which is typified by small consistent drop sizes. Convective precipitation occurs in conjunction with stratiform precipitation but is significantly more intense rainfall, accounting for ~70% of total rainfall in a given storm [24]. A 2013 study was conducted on 5-minute rain rates across Germany to understand the types of precipitation that are increasing with temperature. This study concluded that, "Total precipitation follows the temperature dependence of the stratiform type at lower temperatures and closer to that of convective precipitation at the higher temperatures" [25]. Figure 8 demonstrates this convective trend as total rainfall significantly increases with higher temperature [8].

This increase in convective rainfall due to temperature increases will make short term storms (< 24 hours) more intense and lead to increased flash flood events with a potential "featureless temperature dependence at higher temperatures (>20℃)" [25]. The links between precipitation and temperature also follows the seasonal cycle, concentrating storms during the months of April to September. The ties between increased convective precipitation and temperature rise is predicated on the fundamental notions of atmospheric sciences, but is still largely investigative science due to the lack of data modelling [8]. These fundamental science methods are outlined below with the Clausius Clapeyron equation (Equation 1).

A 2014 study conducted by Westra et al. found that for each degree Celsius of globally averaged temperature annual maximum rainfall intensity increases from 5.9 to 7.7% [8]. This finding is not unexpected as the Clausius Clapeyron equation used as a basis of precipitation analysis directly relates the water capacity of a gas to temperature.

$$\frac{1}{e_s}\left(\frac{de_s}{dT}\right) = \frac{L_v}{R_v * T^2} \quad (1)$$

This central equation asserts the temperature dependence of saturation vapor pressure and, "describes the consequences of global warming for the water-holding capacity of the atmosphere" [11]. L_v is the latent heat of vaporization ($2.5 \cdot 10^6$ J/kg) and R_v is the gas constant for water vapor (461 J K^{-1} kg^{-1}). This positive correlation between temperature (T, Kelvin) and saturated vapor pressure (e_s, Pascals) stated by the Clausius Clapeyron equation gives a basic understanding of how temperature increases will increase the saturated vapor pressure very rapidly (as it is not a linear relationship). This in turn allows warm air to hold more water vapor than cold air, increasing precipitation significantly. Research into increased humidity is currently limited by available datasets but has been found through precipitation data.

A 2015 study using over 30 years of hourly precipitation data from Switzerland was conducted to understand precipitation's relation to relative humidity. This study found that towards the summer months, there was a shift in climatic trends where relative humidity remained constant or increased even as warming slowed [26]. This contrasted with the winter months that revealed very low relative humidity levels. While the relation between increased precipitation and relative humidity is evident, the scaling of precipitation compared to relative humidity is complex and varies at higher temperatures [26]. As per the Clausius Clapeyron equation, there are significant ties between the two as the 2015 study shows, but additional research in this field would more strongly support precipitation's fluctuations with relative humidity.

2.3 The Baltimore Region

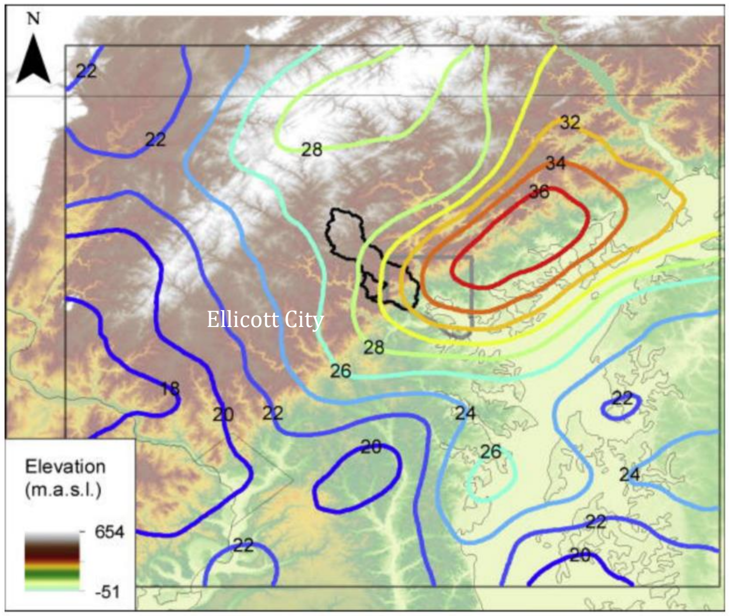

Figure 9.
Baltimore Region outlined in gray; Mean Daily Rainfall (mm) Extreme – Mild (Red – Purple)

The above figure from a 2012 analysis on the use of a long-term high resolution radar around the Baltimore region demonstrates how urban areas can effect extreme rainfall [7]. The gray outline shows the city of Baltimore, with the corresponding colored lines indicating mean daily rainfall averages using 15-minute rainfall measurements. This diagram demonstrates similar patterns seen in Atlanta, St. Louis, Charlotte and Indianapolis: that cities effect rainfall patterns with higher concentrations of rain downwind of the urban area. The climatology of this region is shown through this high spatial resolution of a major city and demonstrates the temperature relations [7]. Ellicott City is shown on Figure 9 and is upwind of the most extreme precipitation that results from the city of Baltimore.

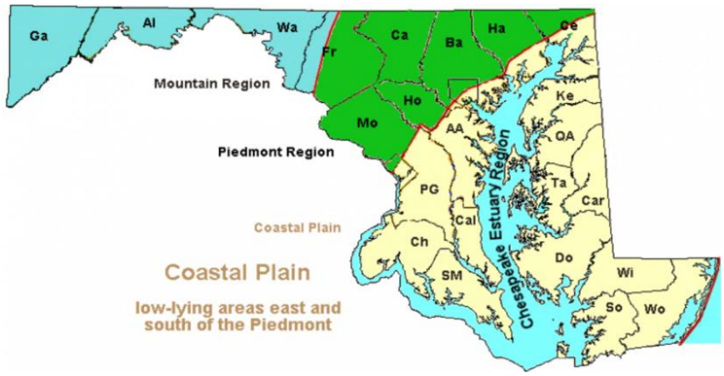

Figure 10.
Maryland Coastal Plain & Piedmont Province

Historic Ellicott City was founded in 1772 and sits just southwest of Baltimore, MD [16]. Ellicott City is known to be a prominent milling and manufacturing town on the East Coast and served as the first commercial railroad station in the US [27]. This historic city is in the Tiber-Hudson Watershed on the edge of the Patapsco River within Howard County. It is surrounded by three principal tributaries with approximately five square kilometers basin areas that make up the drainage zone. Baltimore County is additionally split by the fall line with Ellicott City, next to the fall zone of the Piedmont Province (old hard rock) and the Coastal Plain Province (sedimentary soft rock) as shown in Figure 10.

Both the tributaries and geology give way for Ellicott City to be a very poorly located town in terms of withstanding storms and natural flows. With the May 2016 flood contributing over 6 inches of rain and 1000 emergency calls within the timeframe, this historic town is clearly not designed to withstand massive floods [28]. The 2016 3-hour Ellicott City storm was given a return interval of 1000 years [16]. This asserts that the probability of a storm of this magnitude occurring each year is .1%, highly unlikely. Since a storm of the same magnitude occurred in May of 2018 within the same storm length intervals, it is probable that this original estimate of 1/1000 is inaccurate.

This NOAA probability was found based on Ellicott City's historical storm data for storms of the same duration. Using historical data may no longer be the most accurate approach for Ellicott City and other urban watersheds. As noted by NOAA in the introduction, non-stationarity is not taken into consideration in the data modelling that was performed to predict the probability of a large storm. This historical data analysis in conjunction with the potential for a changing climate is not ideal for predicting storm return intervals.

In addition to the detailed analysis of Ellicott City, flood mechanisms and mechanics are both a contributor to the design of cities as well as a result of cities being implemented. When a new urban area is introduced to a previously untouched land, impervious surfaces are introduced which changes natural runoff patterns. Ellicott City is interesting as it lies at the intersection of 3 contributing tributaries and has had prevalent storms in the past. Climate change could be a contributing factor to the storm return interval being smaller than anticipated, and in turn will change how Ellicott City and new cities will need to be designed and developed. A 2019 study focused on studying large spatial precipitation found that infrastructure is traditionally built based on Intensity-Duration-Frequency curves, but these curves are determined assuming stationary climate [18]. Although non-stationarity is still an unanswered question, Ellicott City is being remodeled after being overwhelmed by the 2016 and 2018 storms in accordance with the Maryland City plans that have been announced [29]. Other small towns like Princeton are looking to take proactive measures to prevent largescale flooding from affecting their town in such a destructive way. Analyzing how the storms have affected Ellicott City and mitigation strategies as a result of this can provide a framework to apply to existing small urban watersheds such as Princeton, NJ.

Chapter 3: Materials and Methods

3.1 Single-Pol versus Dual-Pol

The National Weather Service (NWS) currently owns and operates 159 Dual Polarization S-Band Radars (Dual-Pol) which were converted from Single Polarization Radars (Single-Pol) in 2012 [30]. Single-Pols only allow for horizontal reflectivity measurements to be taken, which limits the scope of analysis that can be conducted. In 2012 the NWS began updating the Single-Pols into Dual Polarimetric Radars (Dual-Pol) which allows for both horizontal and vertical polarimetric measurements to be recorded [12]. The advantages of this improvement include accuracy, solid vs. liquid identification, the introduction of new radar variables, and drop size distribution visibility among others [31]. A 2013 study conducted by Cunha & Smith analyzed Single-Pol and Dual-Pol datasets to find the difference between their bias and errors. They found that Dual-Pol error varies based on precipitation event and that general error is decreased by averaging data sets over longer time intervals [30]. Thus the 15-minute rainfall rates for the multidecade dataset will be averaged into hourly datasets and three-hour datasets. This will improve accuracy of the data as well as allow a comparison between the three-hour data and our three-hour Ellicott City storms in 2016 and 2018.

$$R = aZ^b \quad (2)$$

$$R = rainrate\ mm/hr$$

$$Z = radar\ reflectivity\ factor\ mm^6/mm^3$$

$$a, b = constants$$

The Z-R relationship given in Equation 2 is the only way of calculating rain rate using Single-Pol, with Dual-Pol being more complex due to the presence of measurements in addition to horizontal reflectivity. R is the rain rate in mm/hr and Z is the radar reflectivity factor in mm^6/mm^3. The classification of the Z-R constants a and b are dependent on the type of storm and location as classified by the NWS. For the Baltimore Region (and other non-tropical regions) the values for a and b are 0.017 and 0.71, respectively [32]. As mentioned above, the Dual-Pol technology introduces new radar measurements, two of which are KDP (specific differential phase shift) and Z_{DR} (differential reflectivity). KDP and Z_{DR} can be used in conjunction with reflectivity in several different combinations to calculate rainfall rate. Some of these relationships are shown below.

$$R = aZ^b Z_{DR}^c \quad (3)$$

$$R = \alpha\, K_{DP}^{\beta} \quad (4)$$

$$Z_{DR} = dBZ_{hh} - dBZ_{vv} \quad (5)$$

Z_{DR} (mm^6/m^3) considers the vertical polarimetric measurements available in Dual-Pol and refers to the horizontally transmitted and horizontally received Z measurements and the vertically transmitted and vertically received Z measurements as per Equation 5. Having a positive Z_{DR} implies a larger horizontal axis rather than a vertical axis for each individual rain drop, meaning larger drops and higher rain rates. Z_{DR} is important for differentiating between hail and extreme precipitation, as hail has a Z_{DR} of 0 and without Z_{DR}, hail and extreme precipitation cannot be differentiated. Since Dual-Pol was introduced in 2012 and overlaps with the available Single-Pol data used in the Baltimore Region (for 3 years of data), the datasets were combined by averaging them (Figure 11).

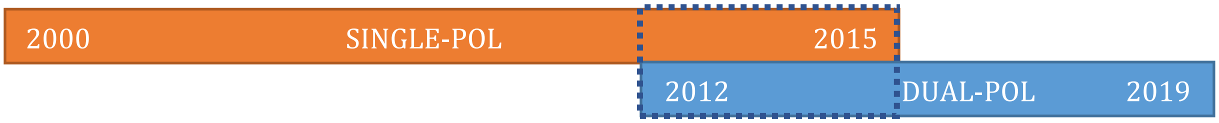

Figure 11.
Overlapping Multidecade Dataset for the Baltimore Region

3.2 Ellicott City Data

The first dataset analysis was performed on the region surrounding Ellicott City using the KLWX radar data. The KLWX radar is in Sterling, Virginia and is a Dual-Pol radar featuring KDP and Z_{DR}. The feed from this radar is shown in Figure 12, with Ellicott City being around 40 miles from the radar location [9].

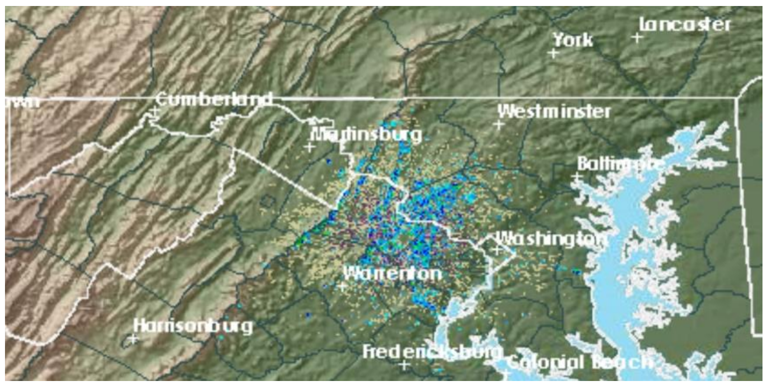

Figure 12.
KLWX Radar Feed, 03/05/2020

This KLWX radar data was gridded to Cartesian coordinates using Py-ART by the Princeton Research Group. The analysis used 0.5 km grid resolution and was based on radar scan time. Rain rate grids were created from the raw polarimetric radar data using the composite algorithm below that was developed by the Princeton Research Group.

Precipitation Algorithm

$\boldsymbol{For}\ (dBZ > 45)\ \boldsymbol{and}\ (KDP > 0.1\frac{deg}{km})$

$$R = 40.5(KDP)^{0.85}$$

Else

$$R = 0.017(Z)^{0.71}$$ [32]

This algorithm is still in the works as additional precipitation research provides insight into accuracy of the algorithm. When Z exceeds 45, rain rates are relatively high, so the KDP equation is used. The R-KDP relationship is the default for this equation as the parameters specified should filter out hail, allowing for rain just below the top of the melting layer to be accounted for [33]. The 'Else' equation is set to the standard Z-R relationship indicated by Equation 2 with constants given from the inversion of the standard NEXRAD formula [32].

Basin Shapefiles were used to make basin average timeseries on radar scan time using the USGS Stream Stats package and ArcGIS. These rain rates were bias corrected using a mean field bias computed from both the Baltimore County and Howard County rain gage networks. These files were then used to analyze individual basin by storm.

3.3 Multidecade Data

The multidecade analyses also use the KLWX radar, as seen in Figure 12. The multidecade record put together by Mary Lynn Baeck was downloaded as Tape Archive files and converted into NetCDF files. This data consists of over 614,000 15-minute records of one km^2 over the 20-year period. These fine spatial measurements were used to create different one hour and three-hour storm equivalents by averaging each 15-minute period into the respective epochs. This allowed for a higher level of accuracy as spatial errors in the measurements can be decreased by averaging over time [30]. Although 12-month datasets were collected for the Single-Pol data (2000-2015), the Dual-Pol measurements (2012-2019) only contain data for the months with highest convective rainfall (April-September). Analysis was thus focused on these 6 months due to the data gap, but it should be noted that analyzing additional months would add more noise than data points due to the concentration of convective rainfall during the warmer period.

The multidecade files are publicly available on the Princeton Hydrometeorology website and were scrubbed to check if there were any anomalies. These anomalies were found only in the month of April 2012 where a few Dual-Pol measurements were recorded and stored in the Single-Pol files. This anomaly could be due to the switching of the systems from Single-Pol to Dual-Pol in April of 2012. Once all the files were scrubbed, they could be converted into 15-minute rainfall rates categorized by month and year.

Many conversion steps were required prior to analysis due to the sheer magnitude of data files that had to be processed. 15-minute rainfall rates categorized by year and month were merged from 614,000 files into 138 files to work with. Once these files were categorized by month, they were resampled as hourly averages to improve accuracy (and again reduce file run time). Additional hourly averaged files with the combined Single-Pol and Dual-Pol files for the 2012-2015 years were created for a methods analysis. These hourly samples were the first round of files that could begin a methods and frequency analysis of rainfall.

The first analysis was conducted between the Single-Pol and Dual-Pol datasets at given timestamps over the differing time ranges (hourly, 3-hourly). This involved both a visual analysis by plotting overlapping datasets throughout the spatial region as well as a dispersion analysis of each dataset. A correlation analysis was conducted by finding the Pearson's Correlation for each Single-Pol and Dual-Pol timestamp and then averaging these monthly. This correlation analysis gives insight into whether the 3-hour or hourly analysis provided more accurate results and how these results differed. The Fisher Transformation was then used to assess significance between these correlation values.

The Single-Pol and Dual-Pol files were then utilized for a frequency analysis using a threshold of rainfall rates. For the years 2012-2015, the Single-Pol and Dual-Pol datasets were averaged at each spatial point such that there was equal weight placed on each dataset.

The years 2000-2011 consisted of only Single-Pol files, with the combined files used for 2012-2015 and 2016-2019 using only Dual-Pol. Combining these datasets provided a coherent multidecade dataset for this project and for future precipitation research. The thresholds explored consisted of 5, 10, 15, 20, 25, 30 and 35 mm of rainfall thresholds for the hourly and 3-hourly averaged datasets. The majority of the months analyzed above 35 mm did not have 3 datapoints to work off of, which would make a derisory analysis. Although this is true for this multidecade dataset, thresholds above 35 mm should be considered for other datasets using these methodologies. This threshold analysis was conducted on hourly and 3-hour averaged datasets created for all of the Single-Pol and Dual-Pol files. This was done by comparing monthly data across years to dampen the impact of seasonal differences.

Trends by magnitude were tracked by comparing the peak at each time stamp in addition to the frequency trends. This was again done using a threshold analysis for both hourly and 3-hourly storms. Spearman's rho and the Mann Kendall Test were then conducted to assess non-stationarity within the threshold periods. These results were categorized by using a 2-tailed p value to assess their significance levels.

This magnitude and frequency analysis will give insight into how the Baltimore Region has changed over time and what can be done to mitigate negative factors of extreme precipitation (flood preparedness) and boost positive factors (sustainable energy systems).

Chapter 4: Results & Discussion

4.1 Ellicott City

Initial analysis of the 5-minute KDP and radar reflectivity fields for the May 2018 storm resulted in spatial maps showing the storms' progression. Pictured below (Figures 13, 14) are maps of the peak rain rate over Ellicott City, which occurred around 21:50 UTC. The timing of this image corresponds with the noted maximal rain rate peak for the 2018 storm.

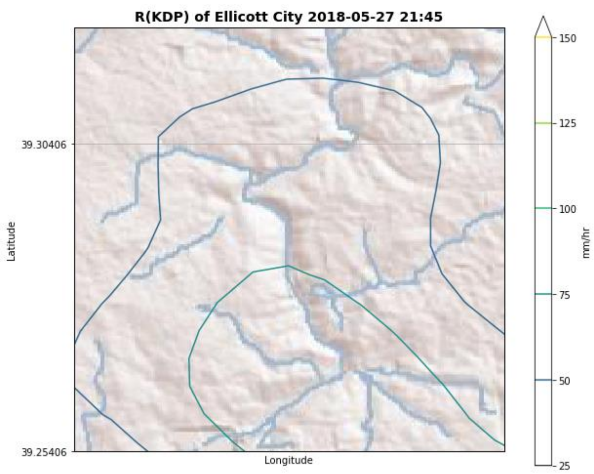

Figure 13.
R(KDP) Measurements at Peak Precipitation

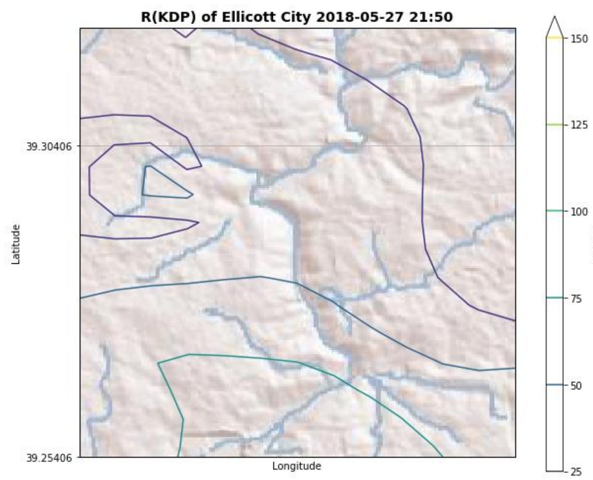

Figure 14.
R(KDP) Measurements at Peak Precipitation

Basin Shapes were calibrated using information provided by Andy Miller and James Smith (Figure 15). The basin shapes that corresponded were then extracted from StreamStats with the assistance of Yibing Su. ArcGIS was used to create the shapefiles below (Figure 16) for use in Python.

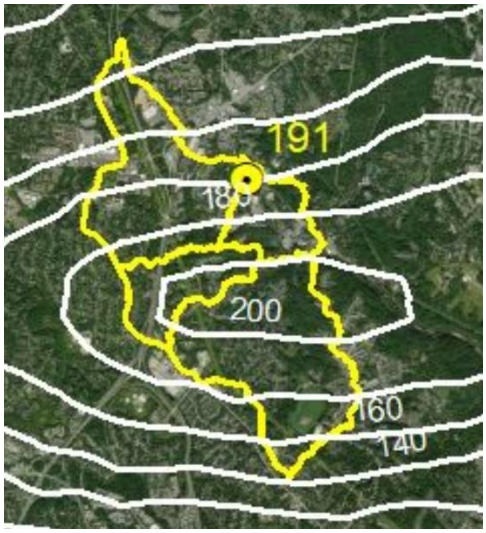

Figure 15.
Basins Surrounding Ellicott City

Figure 16.
Basins Surrounding Ellicott City - Python

The basins were named based on the river flows surrounding each basin giving titles of *Sucker-Hudson, Hudson-Tiber* and *Tiber-Bonnie*. Gridded rainfall rates were basin-averaged using these shapefiles for both the July 2016 (Figure 17) and May 2018 (Figure 18) storms. Both storms were of similar magnitude and length with the 2018 precipitation higher per basin than the 2016 precipitation. The 2016 basin-averaged rain rates totaled: 240 mm (Sucker-Hudson), 219 mm (Tiber-Bonnie), 230 mm (Hudson-Tiber). The 2018 basin-averaged rain rates totaled: 264 mm (Sucker-Hudson), 316 mm (Tiber-Bonnie), 319 mm (Hudson-Tiber).

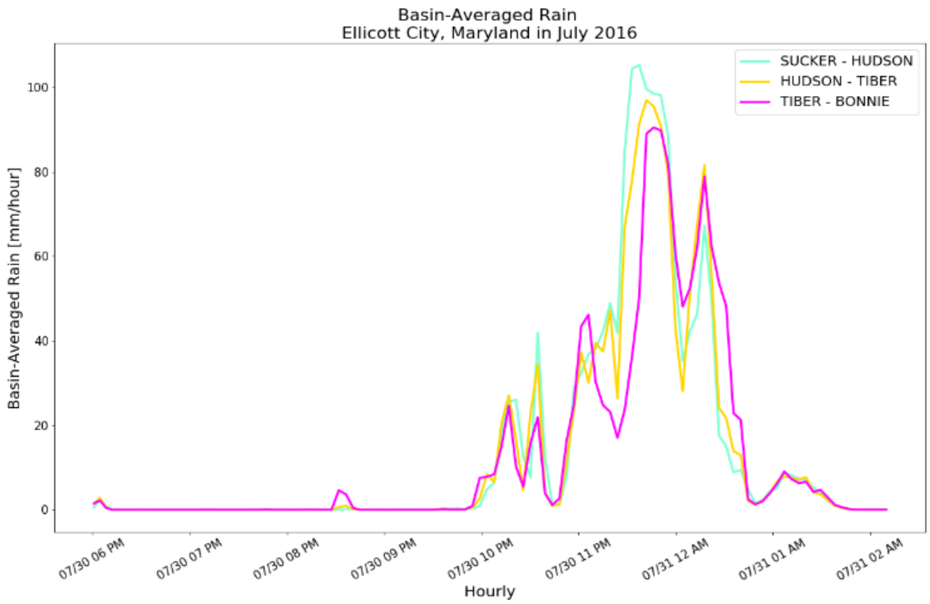

Figure 17.
Basin Averaged Rain Rate 2016

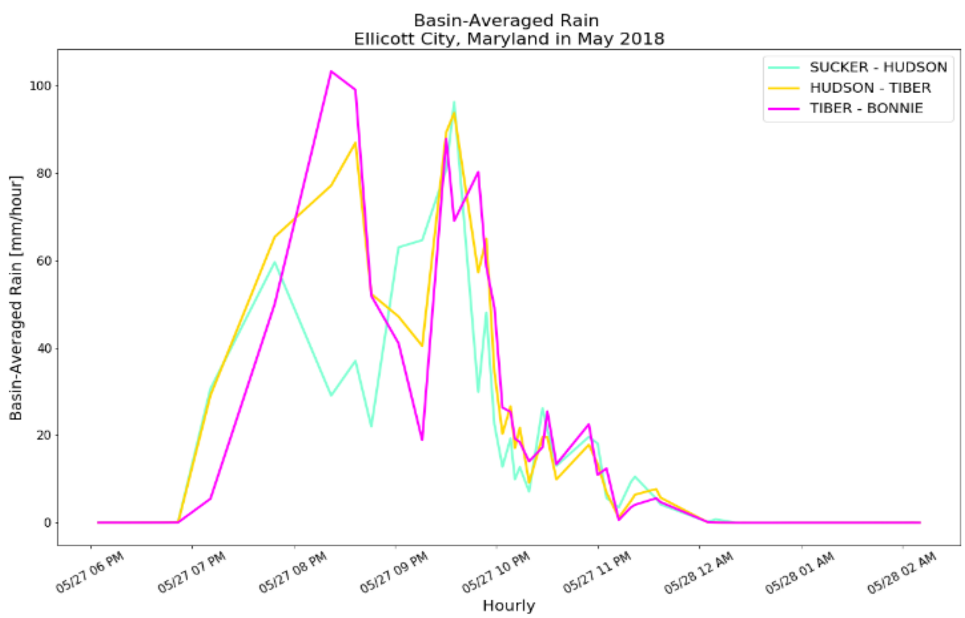

Figure 18.
Basin Averaged Rain Rate 2018

The July 2016 and May 2018 floods were evaluated for frequency of rainfall rate normalized by basin area (Figure 19). The frequency and magnitude of rainfall in the *Sucker-Hudson* and the *Tiber-Bonnie* basins are similar with the *Hudson-Tiber* basin being the only basin with a high frequency of larger magnitude rainfall rates. I hypothesize that this indicates that the majority of flooding is contributed by the *Hudson-Tiber* basin due to the large magnitude of rain entering the city at once.

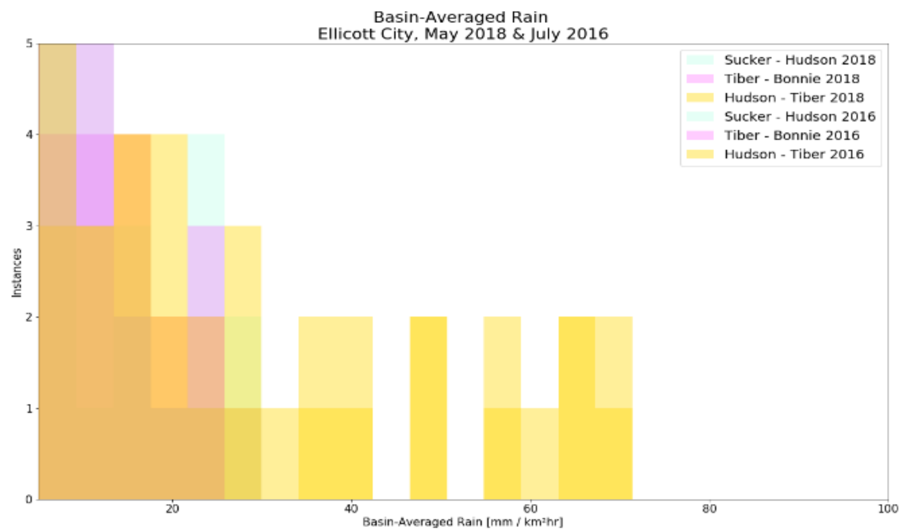

Figure 19.
Frequency / Magnitude by Basin 2016 & 2018

4.2 Single-Pol & Dual-Pol Methods

The Single-Pol and Dual-Pol 15-minute rainfall rates provide the first basis for analyzing the differences between the methods. The correlation factor for each timestamp is important to know for the hourly and 3-hourly averaged datasets to assess if one is more significantly accurate. The methods analysis shown below resulted in finding that the correlation between the Dual-Pol and Single-Pol data does improve by averaging the datasets hourly and 3-hourly. This is demonstrated visually by choosing just one timestamp.

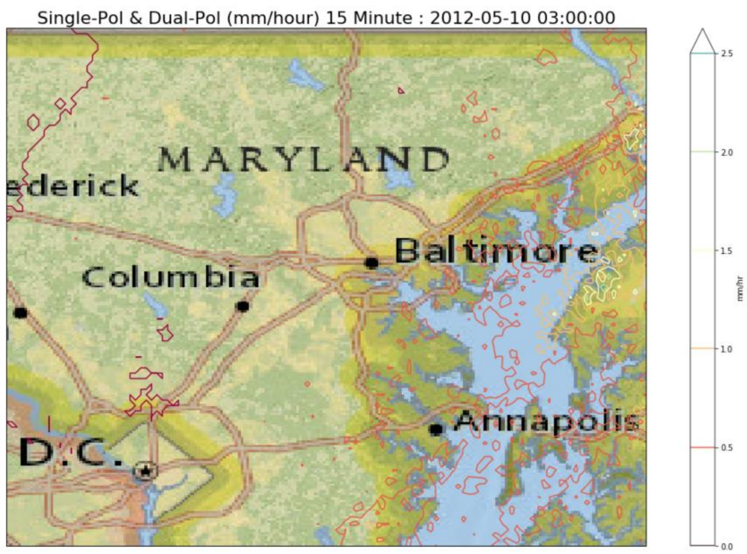

Figure 20.
Single-Pol & Dual-Pol Differences 15-Minute

Figure 20 indicates a timestamp (2012-05-10) that has both Single-Pol and Dual-Pol data available, showing the differences between the measurements. This time was chosen as it is within the convectional rain high season but not during a storm and shows the variations between the two datasets. While both Single-Pol and Dual-Pol show similar results, they contrast spatially and demonstrate that the methods do provide different resolutions. Figure

21 and Figure 22 show the differences between Single-Pol and Dual-Pol using hourly and 3-hourly averaged datasets respectively.

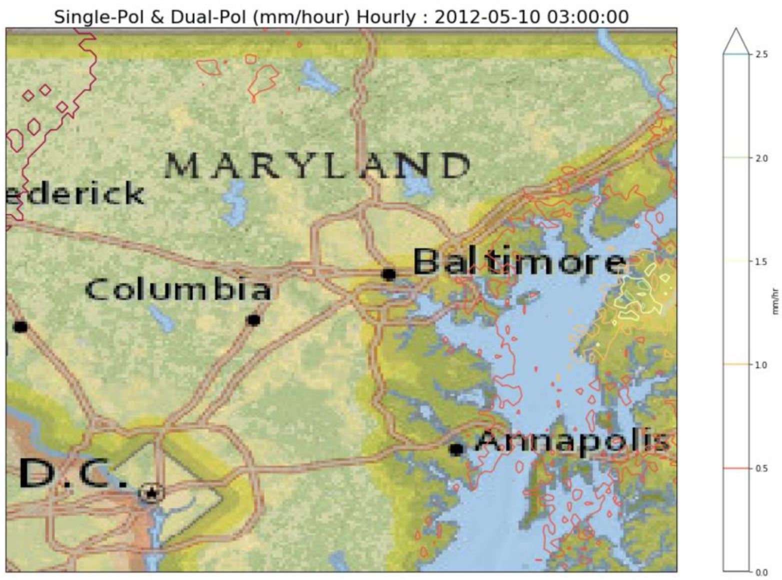

Figure 21.
Single-Pol & Dual-Pol Differences Hourly

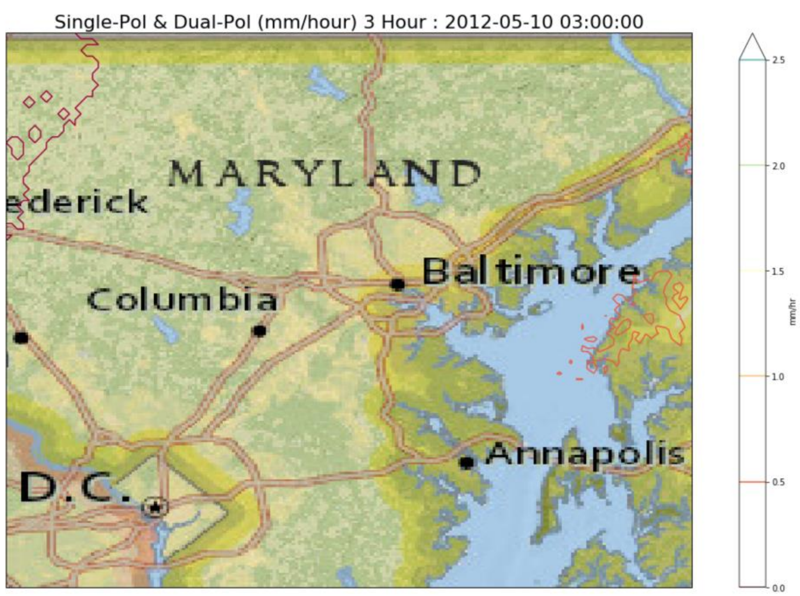

Figure 22.
Single-Pol & Dual-Pol Differences 3-Hourly

As shown in Figure 21 and Figure 22, the Dual-Pol and Single-Pol datasets converge as they are averaged over larger timesteps. This is most obvious below the word 'Baltimore in Figures 20, 21 and 22, with the differences decreasing over larger time averaged datasets. This imaging demonstrates the spatial changes to the datasets between Dual-Pol and Single-Pol, but the dispersion of the datasets shows how much the data can improve with this timescale averaging.

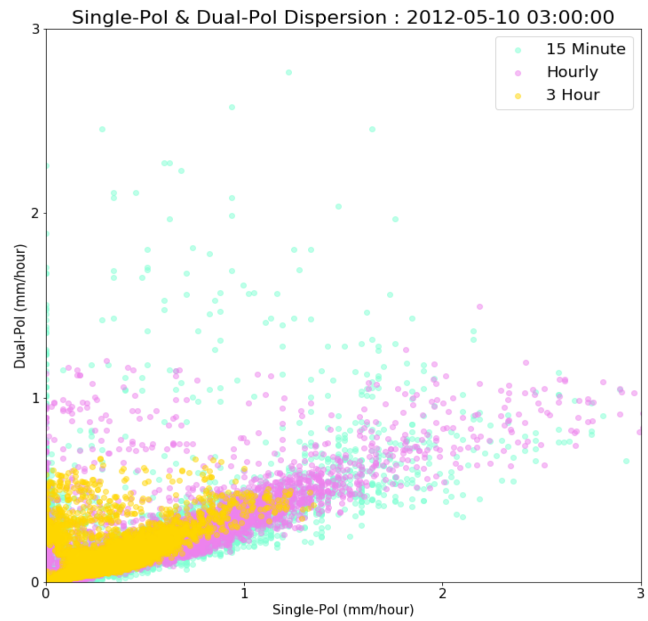

Figure 23.
Single-Pol & Dual-Pol Rain Rate Dispersion

The dispersion of precipitation rates identified per each spatial point (latitude and longitude) in Figure 23 is for the same timestamp in Figures 20, 21 and 22. This dispersion corresponds with the spatial clarity shown in the preceding figures by showing that the accuracy between the Single-Pol and Dual-Pol data converges on longer timescales. To see this trend throughout the dataset (and not just one timestamp), the correlation factor was found for each timestamp possible (every 3rd-hour) for the entirety of the Dual-Pol and Single-Pol overlap and then averaged monthly. This is shown in Figure 24.

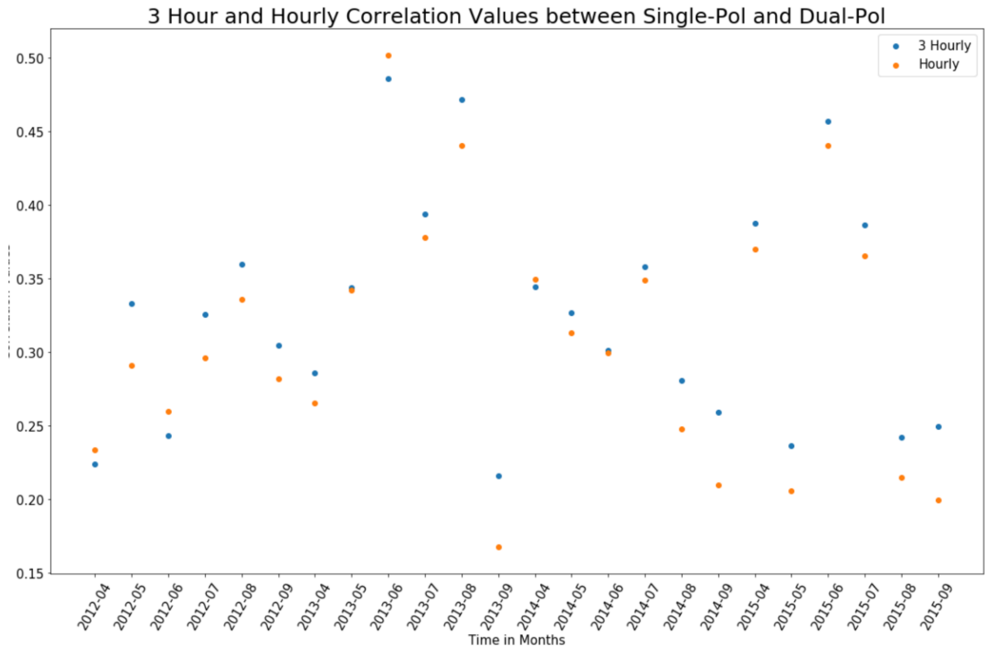

Figure 24.
Single-Pol & Dual-Pol Rain Rate Correlation

As shown in Figure 24, the 3-hour correlation values are overall higher than the hourly averaged values. The mean correlation value for the 3-hour data between the Dual-Pol and Single-Pol data is 0.326 as compared to the mean correlation for the hourly data which is 0.307. While still moderate correlations, they provide a strong basis for the interaction between Single-Pol and Dual-Pol datasets. The 3 Hourly dispersion demonstrates a significantly more in line trend than the one-hour resolution with an 80% Confidence Interval. Thus these Single-Pol and Dual-Pol datasets agree with the findings of Cunha & Smith [30] that averaging the resolution will improve accuracy between the Single-Pol and Dual-Pol findings.

4.3 Multidecade Dataset

The multidecade dataset was analyzed on an hourly and three-hourly basis for maximal peaks as well as total observations above thresholds. These thresholds were 5, 10, 15, 20, 25, 30 and 35 mm for both the hourly and 3-hourly averaged datasets. As mentioned before, results above 35 mm were sparse as the non-stationarity tests require at least 3 data points to do an analysis and multiple months had less than 3 instances. By discounting values below each threshold, it creates less noise around actual storm-related precipitation. Yearly datasets are overlaid by month in Figure 26 A-F for hourly precipitation maximums and are similarly done in Figure 27 A-F for 3-hourly precipitation maximums.

Accounting for yearly averages over each month was done so that the Mann Kendall Test can be applied without seasonal differences impacting it. This is because both Mann Kendall and Spearman's rho are used for identifying increasing or decreasing monotonic trends and are not accurate when impacted by seasonal variations. The 3-hour data shown in Figure 27 demonstrates that there is a higher volume of smaller precipitation data bringing down the average significantly from the hourly data (Figure 26). July, August and June across both the hourly and 3-hourly data displays higher on average data rain rates than the other three months (Figure 25, Figure 26 C-E, Figure 27 C-E).

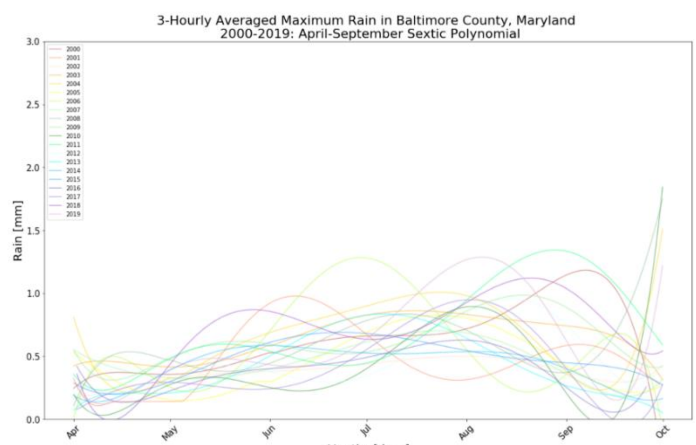

Figure 25.
3-Hourly Sextic Polynomial Season Trends

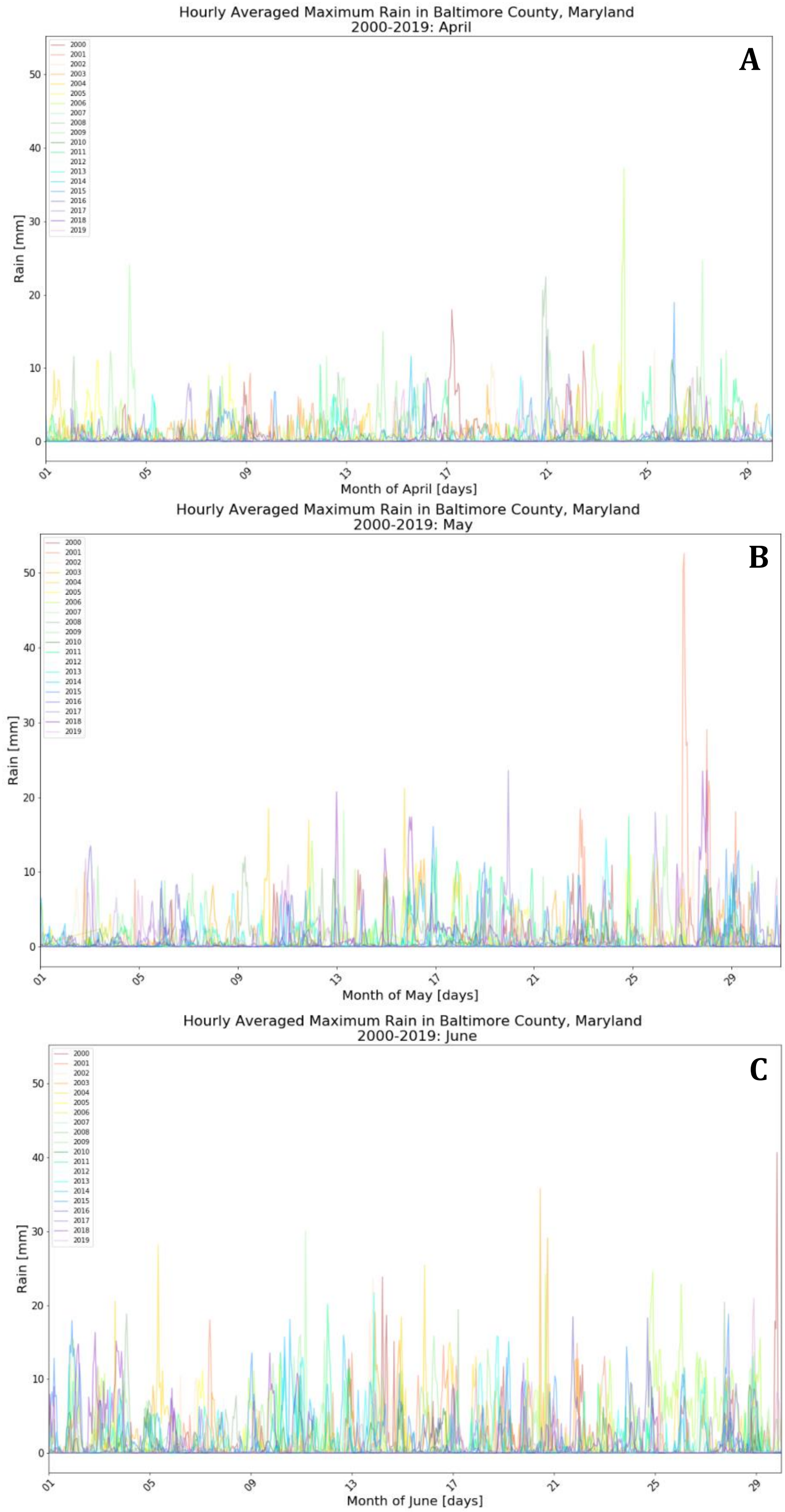

Figure 26 A-C.
Hourly Multidecade Monthly Rain Rates (mm)

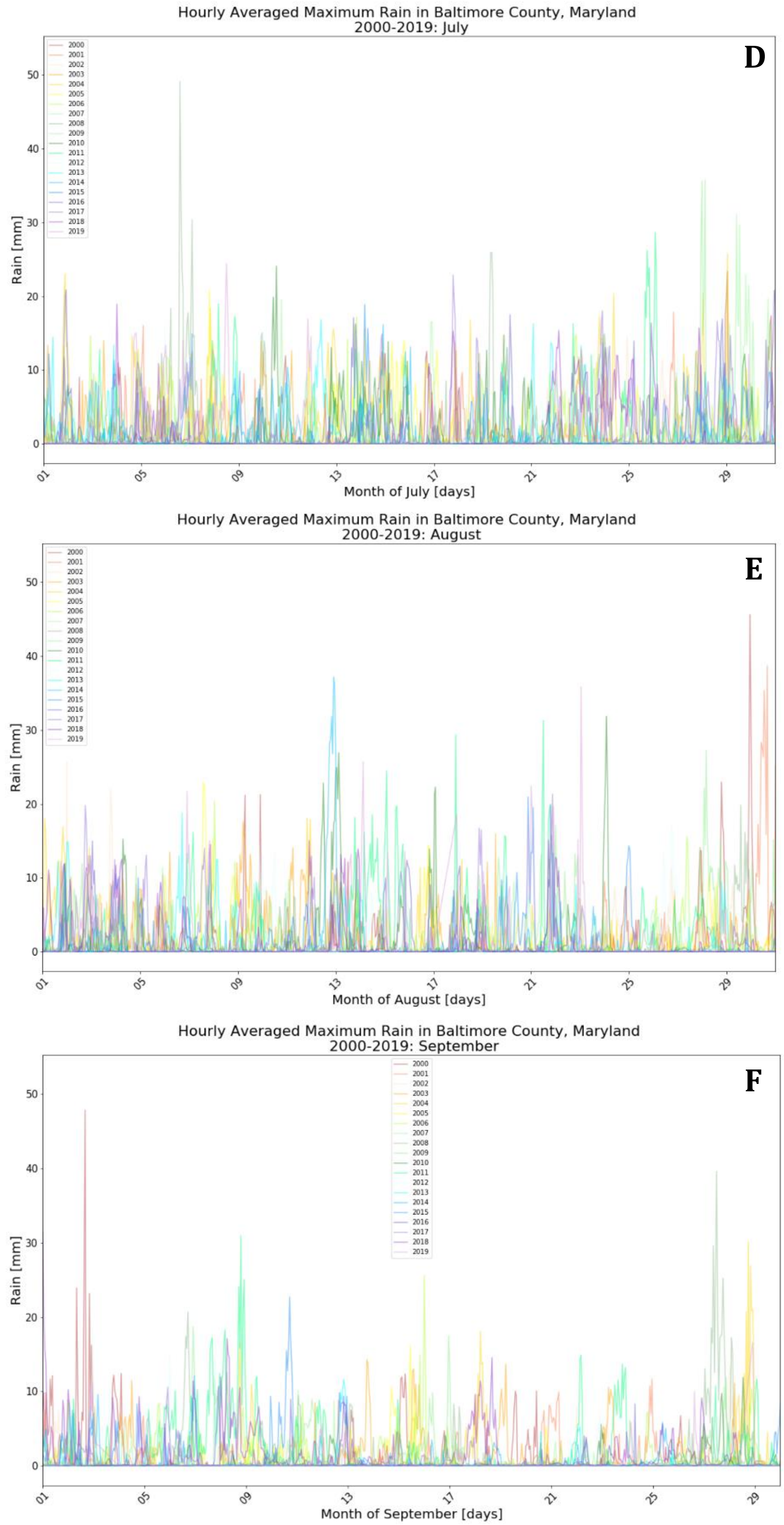

Figure 26 D-F.
Hourly Multidecade Monthly Rain Rates (mm)

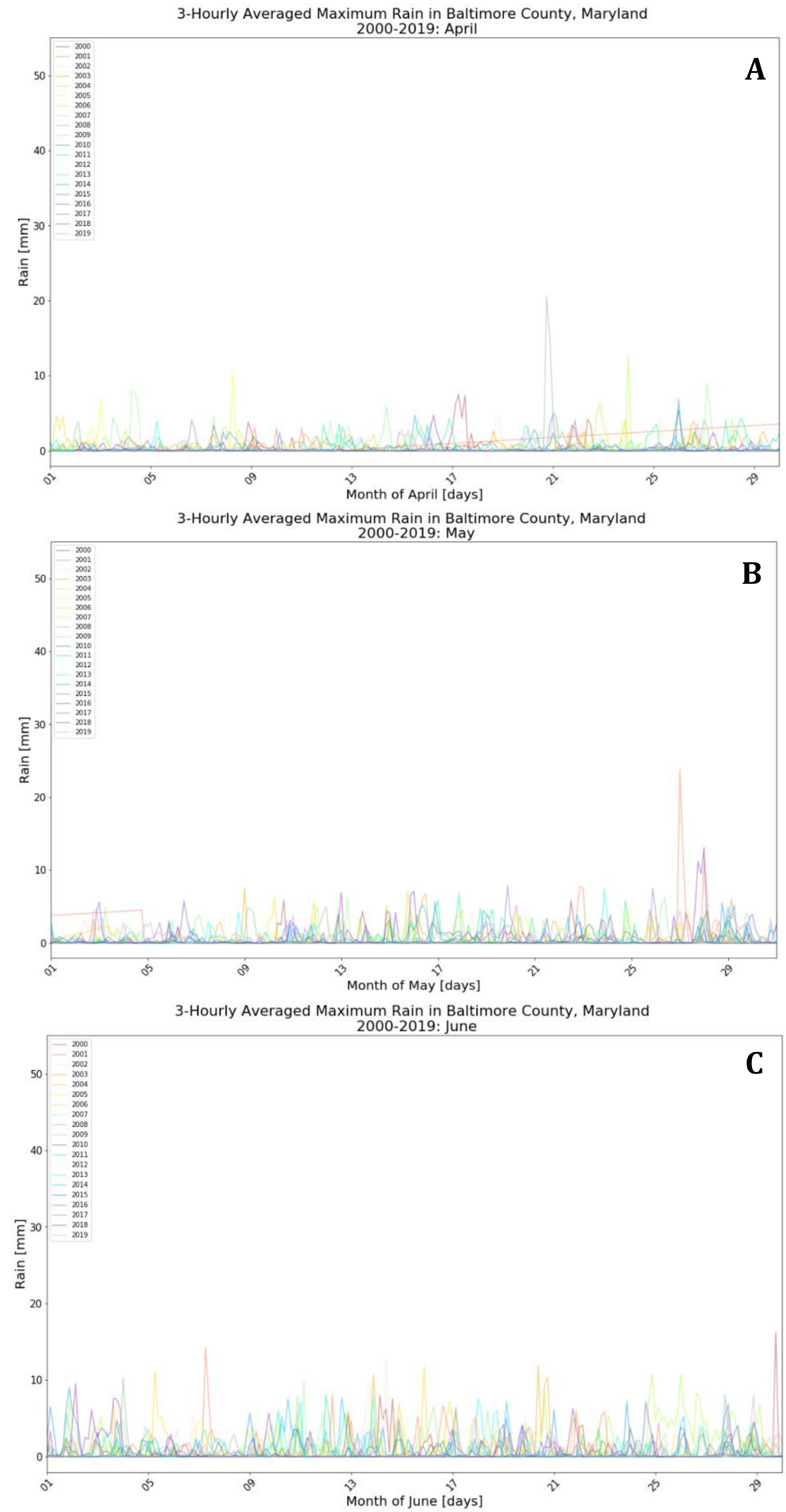

Figure 27 A-C.
3-Hour Multidecade Monthly Rain Rates (mm)

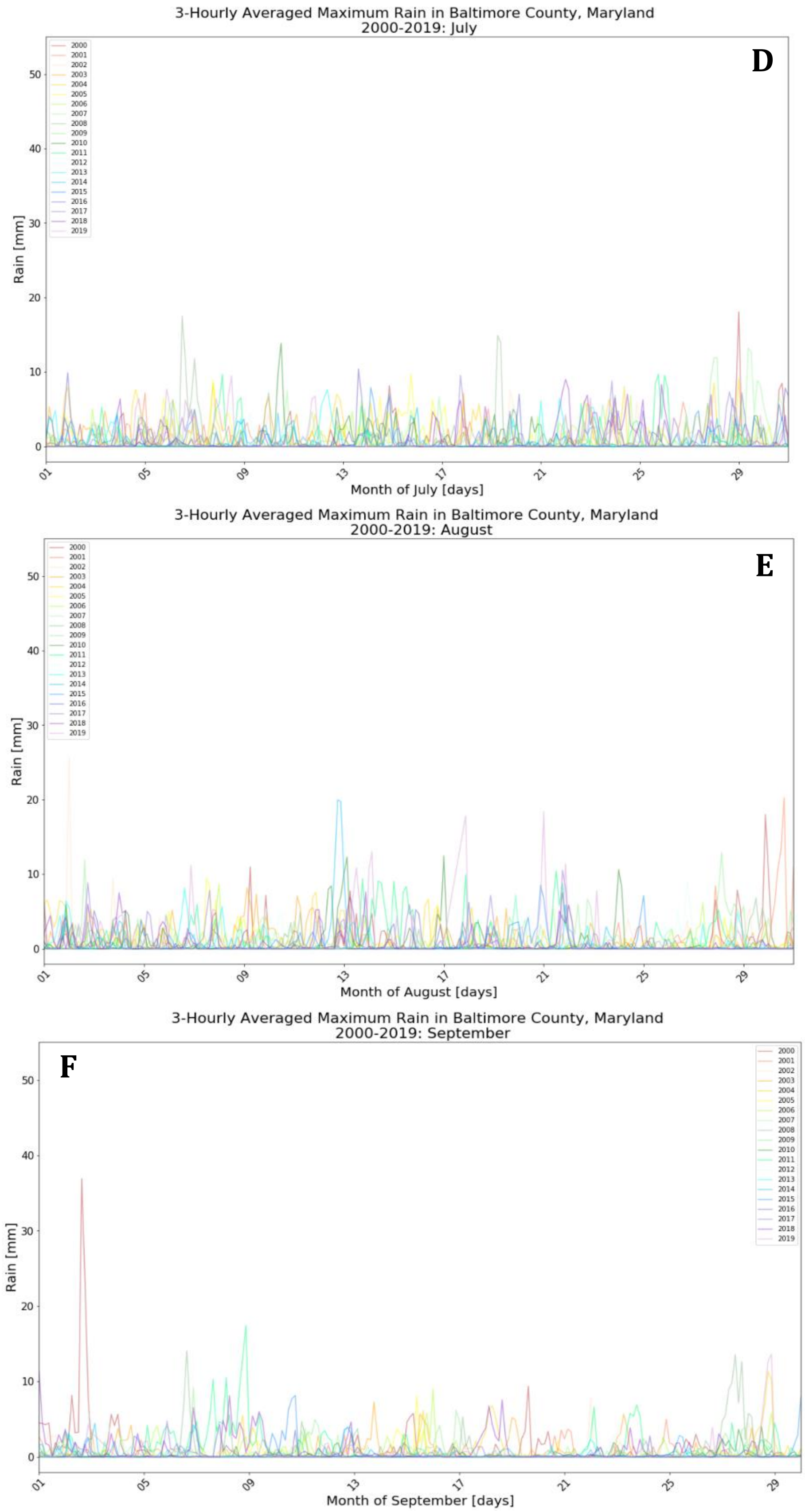

Figure 27 D - F.
3-Hour Multidecade Monthly Rain Rates (mm)

As shown in Figure 27 A-B, 2001 had missing data between the months of April – May. This likely had an insignificant impact on the overall Mann-Kendall results. As shown in Figure 26 A-F there are many large outliers that indicate storms during each month. The 3-hour data shows a bit of a different story though with September having the largest rain rate recorded and the other months significantly lower from that. Figure 26 and Figure 27 together indicate that there were significantly more instances of hour-long storms as compared to 3-hour storms.

Looking back at the Ellicott City dates and mapping these to the overall Baltimore region, Figure 27 C does not indicate significance for the July 2016 storm. The May 2018 storm that occurred in Ellicott City is on the radar in Figure 27 B, demonstrating that the 2018 storm not only impact Ellicott City but occurred over the entire Baltimore Region.

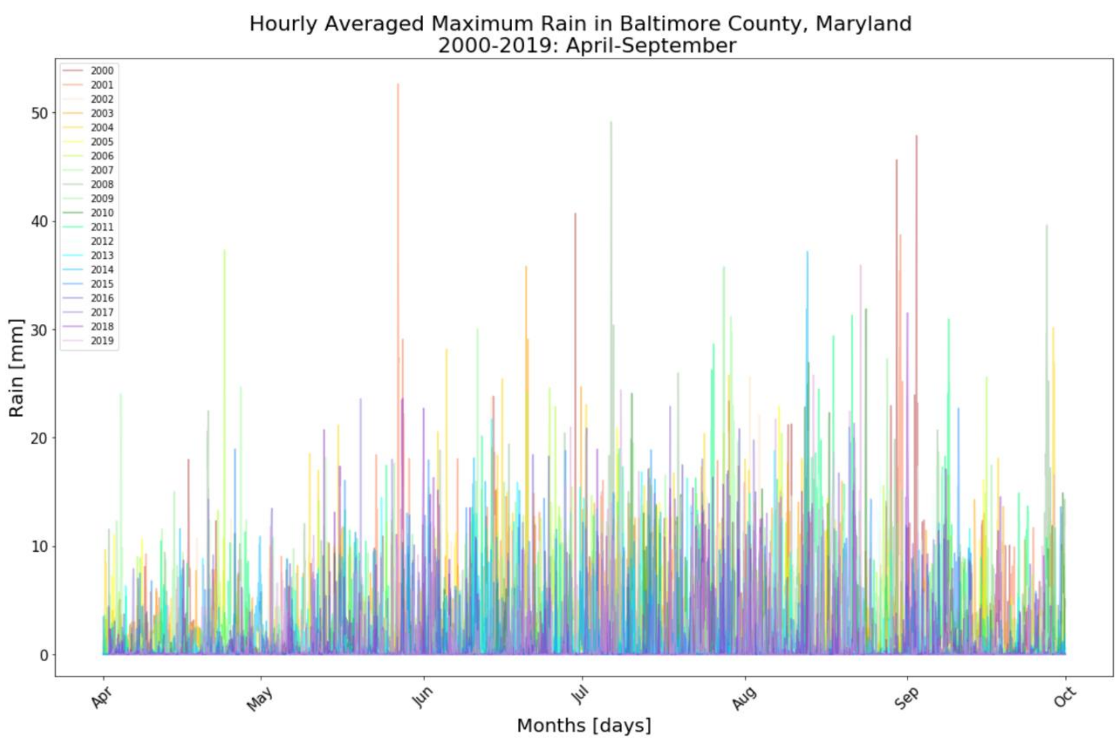

Figure 28
Hourly Multidecade April-September Rain Rates

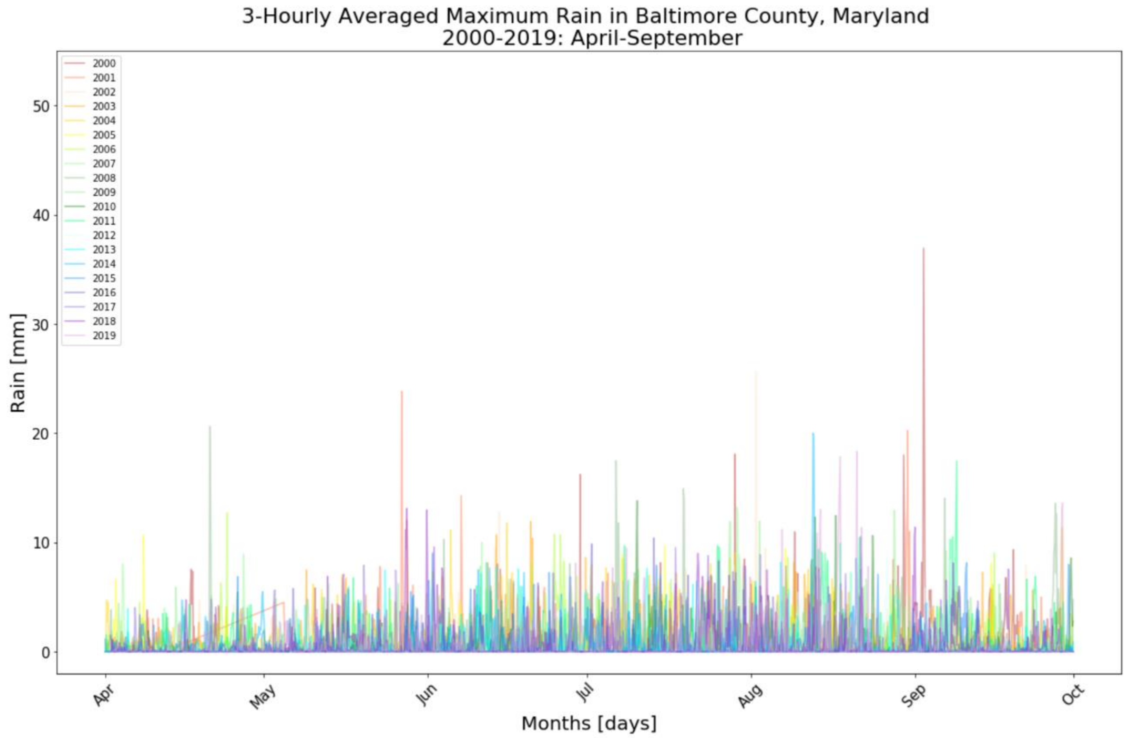

Figure 29
3-Hourly Multidecade April-September Rain Rates (mm)

Figure 28 and Figure 29 show the 6-month period in which data was recorded. As shown in Figure 25, each year varies widely with precipitation amount, but seasonal trends are discernable. The Mann-Kendall and Spearman's rho were found for each month (using 2000-2019 data) at each threshold mentioned. As the thresholds increase, there should be a higher likelihood of indicating positive or negative trends as the data is sparser. The caveat with this is that for some months data decreased rapidly above a particular threshold, which can be seen easily in Table 1 for the 3-hour threshold increases.

Starting with the hourly data shown in Table 1, there is a strong negative trend using both the Mann-Kendall test and Spearman's rho. This indicates that rain rates across all thresholds are decreasing to some extent. This is an indication of non-stationary precipitation patterns within the Baltimore Region. May and June with a threshold of 20 mm are the strongest results with Mann-Kendall taus' of -0.495 and -0.438. Although there are larger correlations within the dataset, the uncertainty of these two (0.016, 0.012) indicates these correlations are reproducible.

The 3-hour data indicates similar negative precipitation trends over the multidecade period at lower thresholds. In Table 1 within the 3-hour trends, June has a Mann-Kendall tau of -0.667 for a threshold of 10 mm with a 2-tailed p value of 0.003, a strong negative trend with a high confidence interval. Looking at the positive trends within the 3-hour dataset, April above 10 mm shows a strong precipitation increase (tau = 0.667, p = 0.308) with a weak significance.

Table 1 uses maximum rain rate data (mm/hr) at each instance the radar was recording, with trends indicating that overall maxima have been decreasing over the years. While this means that there is less precipitation at any given spatial point and that the overall magnitude of precipitation is decreasing, Table 2 will give insights into if the precipitation is spread out or generally decreasing by looking into the frequency of precipitation.

Months	Thresholds (mm)	Averaged Rain Rates (mm) (Magnitude)					
		Hourly			3-Hourly		
		Mann Kendall Tau	Significance (2 tailed p value)	Spearmans Rho	Mann Kendall Tau	Significance (2 tailed p value)	Spearmans Rho
April	0	0.117	0.000	0.177	0.137	0.000	0.209
May	0	0.041	0.000	0.057	0.052	0.000	0.075
June	0	0.097	0.000	0.141	0.098	0.000	0.146
July	0	0.043	0.000	0.055	0.042	0.000	0.058
August	0	0.056	0.000	0.079	0.062	0.000	0.089
September	0	0.118	0.000	0.176	0.118	0.000	0.176
April	5	0.022	0.607	0.032	0.134	0.398	0.277
May	5	0.017	0.566	0.023	0.072	0.503	0.106
June	5	0.012	0.584	0.018	0.083	0.221	0.119
July	5	0.008	0.688	0.012	0.011	0.846	0.024
August	5	0.056	0.005	0.083	0.060	0.271	0.087
September	5	0.027	0.308	0.042	0.106	0.182	0.147
April	10	0.189	0.057	0.280	0.667	0.308	0.800
May	10	0.042	0.518	0.044	0.200	0.707	0.143
June	10	0.028	0.517	0.044	0.667	0.003	0.783
July	10	0.011	0.747	0.017	0.364	0.115	0.448
August	10	0.021	0.545	0.036	0.045	0.734	0.033
September	10	0.045	0.373	0.063	0.099	0.661	0.152
April	15	0.238	0.235	0.307			
May	15	0.311	0.012	0.398			
June	15	0.168	0.061	0.260			
July	15	0.088	0.193	0.124			
August	15	0.038	0.532	0.061	0.357	0.266	0.476
September	15	0.195	0.035	0.269			
April	20	0.357	0.266	0.571			
May	20	0.495	0.016	0.692			
June	20	0.438	0.012	0.567			
July	20	0.057	0.634	0.071			
August	20	0.003	0.981	0.004			
September	20	0.029	0.880	0.061			
April	25	0.000	0.000				
May	25	0.467	0.260	0.714			
June	25	0.600	0.133	0.657			
July	25	0.026	0.951	0.016			
August	25	0.027	0.870	0.031			
September	25	0.061	0.837	0.063			
April	30						
May	30	0.333	1.000	0.500			
June	30						
July	30	0.200	0.707	0.200			
August	30	0.222	0.466	0.217			
September	30	0.200	0.806	0.300			
April	35	0.000	0.000				
May	35	0.000	0.000	1.000			
June	35	0.000	0.000	1.000			
July	35	0.333	1.000	0.500			
August	35	0.467	0.260	0.429			
September	35						

Table 1

Mann Kendall Results: Averaged Rain Rates

Black = Positive Trends, Red = Negative Trends

The frequency of rainfall within the Baltimore Region is measured by total observations above a specific threshold. While the magnitude is found by finding the maximum spatial point at a given time, it does not indicate if that maximum is an outlier at the time or if potentially each point was close to that maximum. Frequency shows the spread of rainfall over the entire region to give a full picture of the historic precipitation data.

Table 2 shows the frequency trends by hourly and 3-hourly precipitation results. The hourly observations from Table 2 indicate a weak negative correlation with varying significance. This indicates that frequency trends are relatively stagnant for hourly observations and that spatial spread has not changed significantly since 2000. Looking at 3-hour observations, Table 2 shows that there were more instances of high precipitation above the 10 mm threshold than Table 1 indicated. This means that 3-hour precipitation has a larger spatial spread (an increased frequency) of precipitation rates above 10 mm. The 3-hour precipitation observations indicate that frequency has remained relatively stationary since 2000.

As thresholds increase for both hourly and 3-hour precipitation, Table 2 demonstrates constant weakly negative correlations for each month. This could be due to the sparse data as the thresholds increase, but again demonstrates that frequency is relatively stationary. Table 2 additionally demonstrates the lack of positive frequency trends – extreme storms are not increasing. Interestingly, the hourly results in Table 2 for the months of May and July (both when the Ellicott City storms occurred) there is a weak increase in frequency of storms up until the 20 mm threshold. This monthly analysis removes the seasonal bias and demonstrates with high significance that frequency of extreme precipitation within the Baltimore Region is not increasing.

Months	Thresholds (mm)	Averaged Observations (#) (Frequency)					
		Hourly			3-Hourly		
		Mann Kendall Tau	Significance (2 tailed p value)	Spearmans Rho	Mann Kendall Tau	Significance (2 tailed p value)	Spearmans Rho
April	0	0.011	0.051	0.016	0.011	0.247	0.016
May	0	0.070	0.000	0.102	0.069	0.000	0.101
June	0	0.011	0.049	0.016	0.015	0.117	0.021
July	0	0.016	0.004	0.025	0.019	0.050	0.029
August	0	0.082	0.000	0.117	0.086	0.000	0.124
September	0	0.144	0.000	0.207	0.145	0.000	0.211
April	5	0.026	0.000	0.032	0.024	0.043	0.030
May	5	0.025	0.000	0.031	0.000	0.971	0.001
June	5	0.013	0.046	0.017	0.027	0.024	0.033
July	5	0.027	0.000	0.033	0.017	0.141	0.021
August	5	0.032	0.000	0.040	0.018	0.127	0.022
September	5	0.003	0.611	0.004	0.014	0.223	0.018
April	10	0.016	0.024	0.019	0.013	0.298	0.015
May	10	0.009	0.159	0.012	0.002	0.893	0.002
June	10	0.016	0.022	0.019	0.040	0.001	0.049
July	10	0.011	0.090	0.014	0.009	0.441	0.011
August	10	0.034	0.000	0.042	0.023	0.047	0.028
September	10	0.005	0.443	0.006	0.000	0.973	0.000
April	15	0.013	0.062	0.016	0.005	0.691	0.006
May	15	0.002	0.821	0.002	0.017	0.153	0.021
June	15	0.013	0.052	0.016	0.019	0.115	0.023
July	15	0.007	0.267	0.009	0.016	0.180	0.019
August	15	0.009	0.189	0.011	0.009	0.447	0.011
September	15	0.005	0.468	0.006	0.022	0.064	0.027
April	20	0.009	0.191	0.011	0.003	0.779	0.004
May	20	0.009	0.178	0.011	0.017	0.153	0.021
June	20	0.018	0.008	0.022			
July	20	0.001	0.882	0.001			
August	20	0.001	0.844	0.002	0.023	0.050	0.028
September	20	0.014	0.035	0.018	0.029	0.015	0.035
April	25	0.004	0.533	0.005			
May	25	0.024	0.000	0.029			
June	25	0.017	0.011	0.021			
July	25	0.005	0.481	0.006			
August	25	0.004	0.502	0.005	0.016	0.168	0.020
September	25	0.009	0.176	0.011	0.020	0.085	0.025
April	30	0.004	0.533	0.005			
May	30	0.017	0.013	0.021			
June	30	0.012	0.069	0.015			
July	30	0.004	0.573	0.005			
August	30	0.000	0.995	0.000			
September	30	0.004	0.602	0.004	0.020	0.085	0.025
April	35	0.004	0.533	0.005			
May	35	0.014	0.043	0.017			
June	35	0.013	0.058	0.016			
July	35	0.001	0.829	0.002			
August	35	0.003	0.637	0.004			
September	35	0.009	0.178	0.011	0.020	0.085	0.025

Table 2

Mann Kendall Results: Averaged Observations

Black = Positive Trends, Red = Negative Trends

Chapter 5: Broader Implications

5.1 Energy Policy and Economic Implications

Precipitation trends indicate that there is non-stationarity present in the Baltimore Region from 2000-2019 with a tilt towards decreasing precipitation. Although this is a large temporal and spatial dataset, it should be noted that the results of decreasing precipitation or stagnant results is for this region. This could be an indication of larger nationwide or even a global trend, but more research would have to be conducted to see if these results are an indication of overall non-stationary precipitation. Although precipitation is not increasing (as literature suggested), the implications of these results are still far-reaching with respect to climate change.

Precipitation changes have substantial impacts with the current energy processes in place. Coal quality will be impacted by its moisture content, soil stability would become more variable, and NPP of feedstocks would become more inconsistent [23]. Relocation of major resources such as oil and gas, nuclear power, biomass production, and thermal power would have to be considered as a result of higher flooding or drought risks [23]. Windmills would largely be affected by water level rise (both river and sea). Hydropower would be affected by the altered runoff cycle and would affect its generating capacity as its storage capacity and head would no longer match the expected amounts. Overall, precipitation deviations lead to increased uncertainty, increased variability and increased vulnerability for meeting energy demands [23].

This brings into question how we address climate change as we look to the United States to be a global leader on this topic. There are different approaches to addressing climate change both in the forms of proactive and reactive policies and energy implementations. Our current policy is a reactive one, focusing on the long-term impacts of climate change and slow but steady progress towards a greener future:

> *"The global governance of energy has been confined to long-term planning, identification of trends in the energy markets and buggering of price shocks, rather than focused on providing energy security as a public good and preventing further climate change as a public bad."*
>
> — *Energy Policy and Security under Climate Change, 2018* [34]

The main backing against our current policy asks for ecological economics to be considered as a means for a more proactive response. Ecological economics treats the biosphere as an input to our economic system, creating more clearly the dependence of our economy on available resources [34] [35]. This in turn supports a de-growth economy such that resource scarcity is decelerated, and demand and consumption is controlled [34]. This de-growth economy would not work under capitalism and does not support the current system that businesses and economists use to assess future growth. Planned contraction of growth is meant to be a sustainable solution to a culture built on overconsumption, but the current pandemic due to COVID-19 has introduced potential new insight into policy solutions for climate change that do not involve a drastic alteration into a de-growth economy.

COVID-19's disruption of social norms and the economy has shifted the climate policy debate into a public health debate. This is due to the immediate threat that COVID-19 poses to the United States, as compared to the perceived long-term threat that climate change poses. While COVID-19 has introduced an unplanned contraction into the economy, the United States multi trillion dollar stimulus packages displays a show of political will that climate change will likely impose eventually. At the time of this paper, these packages have ranged from 1 – 3 trillion dollars. This provides hope for climatologists that when push comes to shove, short-term energy policy and ecological economics will come to fruition.

Another indicator of positive social norms changing comes from the stay at home protocols implemented as a result of COVID-19. These protocols have decreased use of the travel sector, closed businesses and decreased consumption in many areas. Orders in states to only make 'essential' trips have decreased overall movement around the US and abroad, as this order effects everything from non-essential shopping to traveling for pleasure. Although this time is uncertain and unprecedented, these changes in social norms show that there could be potential climate change mitigation by a natural reduction in consumption. After the stay at home order is lifted there could be a drastic increase in consumption immediately, or a slow level of increase due to continued fear of COVID-19. What this pandemic has shown is that as a nation we can come together and alter our social norms for the greater good, and the hope is that if reduced consumption is necessary for climate change mitigation, it is highly probable that social norms can be altered similarly. While this pandemic has proven to be a large scale showing of a proactive response to COVID-19 it has a driving force that climate change currently does not, which is an impact on the economy.

The reason there is long-term energy policy in place for climate change is that there is no direct or instantaneous impact on the economy. With the many parallels that COVID-19 has with climate change, the economic scene is likely to be similar if climate change were to become more immediately impactful. As one article states about the pandemic, "Not even during the Great Depression and the second world war did the bulk of the economic activity literally shut down, as it has in China, the US and Europe today," [36]. If climate change were to impact the world in a large way, it would happen swiftly, and the economic downfall would be rapid. With this in mind, similar reactive responses are likely to come into play such as a stimulus plan, immediate and effective energy policies and a scientific rush to further study geoengineering. While this may seem that there is only a truly effective response for some type of life-threatening climate change scenario, proactive efforts on a larger scale are becoming more prevalent because of effective research.

Energy policy shifts are seen from prominent economic players such as BlackRock, one of the world's largest investment management companies. In a January 2020 letter to shareholders, BlackRock CEO Larry Fink wrote, "Awareness [of climate change] is rapidly changing, and I believe we are on the edge of a fundamental reshaping of finance… Research from a wide range of organizations … is deepening our understanding of how climate risk will impact both our physical world and the global system that finances economic growth," [37]. This letter additionally included how BlackRock is planning to integrate sustainability practices into portfolios and adding sustainability risks into investments. Other prominent financial firms such as Morgan Stanley, Goldman Sachs and Charles Schwab have additionally promoted their ESG (Environmental Societal and Governance) investing goals through ESG related web pages.

While these may seem like small steps, it shows an alternative solution to a de-growth economy and suggests that current capitalism can account for climate change. As mentioned by BlackRock, research is the key to continue and increase this ripple effect. Research into all aspects of climate and energy processes are important indicators of climate change and brings new insight into both the discussion of climate change as well as energy policy. While the implementation of new technology around the Baltimore Region has given enormous insight into the precipitation trends over the last 20 years, the analyses used here can shed light on trends within different regions. Research that is conducted today can incrementally alter how climate change is discussed within the environmental, political and economic spheres. Environmental research is a pillar of these important discussions and should continue to be conducted to promote change through economics and energy policies.

Chapter 6: Summary, Conclusions & Future Work

6.1 Ellicott City & The Baltimore Region

Ellicott City was devastated in both 2016 and 2018 by two short-term extreme rainfall events that have led to suggestions that there is non-stationary precipitation in the Baltimore Region. Rainfall data from these two storms are analyzed using 15-minute basin averaged rain rates to determine if there was a particular basin from these storms that was contributing the majority of flooding. A multidecade dataset using 15-minute rain rates from both Single-Pol and Dual-Pol radars was compiled. Accuracy of Single-Pol and Dual-Pol datasets was assessed by comparing hourly and 3-hourly averaged rainfall rates. The Mann-Kendall test and Spearman's rho was used to assess non-stationarity over the 20-year period (2000-2019) monthly using both hourly and 3-hourly averaged rain rates. The primary conclusions of this thesis are outlined below.

Ellicott City's three basins (Sucker-Hudson, Hudson-Tiber, Tiber-Bonnie) demonstrated similarities throughout the July 2016 and May 2018 storms. The Sucker-Hudson and Tiber-Bonnie basins showed similar frequency and magnitude with the Hudson-Tiber basin showing significantly larger magnitudes of rainfall rates. This difference indicates that the Hudson-Tiber basin contributed the majority of flooding issues within Ellicott City as the largest amount of rain entering the city at once was from this basin. Additional research would need to be conducted to determine if this correlation forms a pattern and can then further inform urban planners of the best flood mitigation strategy. Urban planners can then expect that variable weather is increasing and can better anticipate the variations by creating flexible designs for the urban areas with research like this to back up the funding. Moving new buildings to higher ground and limiting impermeable surfaces will additionally reduce flood risks.

The multidecade dataset providing high spatial and temporal resolution within the Baltimore Region shows that the 3-hourly averaged rainfall rates between Single-Pol and Dual-Pol have a higher correlation than the hourly averaged rainfall rates. The 3-hourly mean correlation is significantly more accurate (CI 80%) between the Single-Pol and Dual-Pol radars. These results align with the findings of Cunha & Smith [30] and further support the idea that averaging the high resolution datasets over larger time intervals will provide more accurate results.

The multidecade dataset (2000-2019) from the Baltimore Region does not demonstrate increasing precipitation patterns for frequency or magnitude either on an hourly or 3-hourly timescale. This finding is not in line with previous understandings of the ties between temperature and humidity but provides new insight into potential alternative climate variations as a result of climate change. The effects of temperature and humidity can be variable depending on the type of precipitation (convective versus stratiform) and would need to be further researched to find more significant ties. These stagnant or decreasing precipitation patterns still have negative consequences with regards to climate change and energy processes. Applying these same analyses on other regions would further solidify the understanding between non-stationary precipitation and climate change.

This thesis provides further research into precipitations links with climate change and the importance of its study. Variable precipitation effects energy processes (coal moisture content, cloud cover, hydropower), agricultural processes (soil moisture) and everyday life (floods, extreme storms). To fully answer the questions posed by Senator Benjamin Cardin more research would need to be accumulated so a clearer picture can be formed. The best way to further understand its links with additional variables such as temperature, humidity and the effects of stratiform vs. convective rain is to continue examining precipitation on both a small and large scale. Using high spatial resolution data provides new insights into how environmental variables such as precipitation or flooding are changing on smaller scales. While this thesis lays the groundwork for future analysis within the Baltimore Region, it is research like this that provides the support for arguments that move social, economic, legislative and global change.

6.2 Future Work

Ellicott City had 30+ CCTV video cameras installed around the city following the July 2016 storm. These cameras fully document the 2018 storm and subsequent flooding around the city. The next step in working with the Ellicott City data would be to use Particle Image Velocimetry (PIV) to create hydrographs of the May 2018 storm. Taking these visuals and creating hydrographs would be very useful for multiple reasons.

- Compare basin averaged rain rates with PIV to see if Tiber-Hudson basin contributed the most rain
- Rainfall rates in comparison to flow and flood time would give more accurate time periods for emergency mitigation
- Flood drainage can be assessed to find the major sources of water removal and to potentially enhance these sources as a means of flood mitigation

Additional work can be done to further confirm the Single-Pol and Dual-Pol analysis by comparison with rain gage data. This would assist in pinpointing where the data begins to diverge, as I hypothesize that time averaging the data is not a linear function but rather a quadratic function. As the datasets continue to be averaged, the high spatial and temporal resolution is lost, so finding the right balancing point is important for future analyses. This can be done by applying the methodologies created in this thesis to hydrological datasets from any region or time period for assessment.

It is important to understand the differences between large- and small-scale datasets to evaluate accuracy of these datasets at different resolutions. While NOAA does provide analysis for smaller areas (such as the Baltimore Region), that analysis could be conducted using satellite imaging or datasets that are averaged over some larger spatial region. While this type of analysis is useful, it does not provide the high level of accuracy or depth that can be taken from a high-resolution small-scale dataset. It is imperative to conduct corollary studies using higher resolution datasets within smaller regions to ensure there is accuracy and alignment with larger spatially averaged studies. Soil moisture, flooding, and even sea level rise are all important aspects to assess using hydrological datasets and each should be examined on both large and small scales.

Chapter 7: Appendix

7.1 Supplementary Equations

$$K_{DP} = \frac{1}{2}\frac{d\theta_{DP}}{dr} \quad (6)$$

$$\approx \frac{1}{2}\frac{\theta_{DP}(r_2) - \theta_{DP}(r_1)}{r_2 - r_1} \quad (7)$$

$$\theta_{DP}(r) = \theta_{hh}(r) - \theta_{vv}(r) \quad (8)$$

$\theta_{hh} = transmit\ horizontal, recieve\ horizontal$

$\theta_{vv} = transmit\ vertical, recieve\ vertical$

7.2 Notes on Methodologies

Anaconda, Jupyter Notebook and Python Version 3.0 were the main components for the assessment of this thesis. The files used for this thesis are uploaded to GitHub so that they are publicly available for use and assessment for other hydrology datasets. This code is attributed to Erin Gray, Molly Chaney and previous work from the Princeton Research Team.

GitHub Link:

https://github.com/erinsgray/Senior-Thesis

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7.4 Figure References

Figure 1 [1]

Figure 2 [2]

Figure 3 [3]

Figure 4 [3]

Figure 5 [4]

Figure 6 [5]

Figure 7 [5]

Figure 8 [6]

Figure 9 [7]

Figure 10 [8]

Figure 11 Erin Gray

Figure 12 [9]

Figure 13 Erin Gray

Figure 14 Erin Gray

Figure 15 [10]

Figure 16 Erin Gray

Figure 17 Erin Gray

Figure 18 Erin Gray

Figure 19 Erin Gray

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Figure 23 Erin Gray

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Figure 25 Erin Gray

Figure 26 Erin Gray

Figure 27 Erin Gray

Figure 28 Erin Gray

Figure 29 Erin Gray

7.5 Table References

Table 1 Erin Gray

Table 2 Erin Gray

7.6 Equation References

Equation 1 [11]

Equation 2 [12]

Equation 3 [12]

Equation 4 [12]

Equation 5 [12]

Equation 6 [12]

Equation 7 [12]

Equation 8 [12]