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Visualizing Extreme Precipitation for Climate Storytelling

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By

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Abstract

Precipitation can have adverse effects in the climate ecosystem. Too much can impose concerns such as flooding and landslides, resulting in damaged property, agricultural losses, and loss of life. Too little, and drought becomes an issue, inducing wildfires, poor air quality, agricultural losses, and health degradation. The contiguous United States has experienced an increase in precipitation since 1900, and much of this has occurred in the most recent decades. By the end of the 21st Century, it is expected that more winter and spring precipitation will occur over the northern portion of the U.S., and less in the southwest. While much work has been performed on historical and projected analysis of heavy precipitation, few interactive visualizations exist for end users to better understand local impacts.

The goal of this project is to create a visualization tool that easily demonstrates how precipitation extremes have changed and might change in the future. The Global Historical Climatology Network-Daily dataset was used to calculate a historical record of extreme precipitation variables at over 3500 locations in the United States. Among these variables calculated are annual accumulation percentiles based on 1981-2010 Normals, annual 1-day and 5-day maximum daily precipitation, and annual consecutive wet and dry days.

Key Words: climatology, climate change, precipitation, climate adaptation

Hyperlink to the Visualization of Precipitation Extremes website:

https://arcg.is/0qmaf8

Acknowledgements

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Special thanks to my undergraduate thesis advisor, Dr. Rowe, and co-advisor, Dr. Anderson.

1. Introduction

A changing climate will bring various changes to society, such as an increase in health-related risks, modified ecosystems, freshwater availability, rising sea levels and economic impacts (e.g. Parry et al. 2007). The warming climate is also expected to influence the amount of precipitation recorded on the globe. Saturation vapor pressure increases exponentially with increasing temperature, s basic moist thermodynamics means that a warmer atmosphere can produce more precipitation. The changing climate can also affect the weather patterns, and in turn, the locations that receive precipitation. This could mean that just as some areas may see more precipitation and become vulnerable to flooding, other areas could see less precipitation and become affected by drought. Drought and flooding regularly make significant contributions to NOAA's list of billion-dollar disasters, accounting for around 23% of total loss due to natural disasters annually (NOAA 2018a).

While the projections for extreme precipitation are expected to increase for most areas in the United States, changes in precipitation amounts are already being observed (Figure 1). According to the 3rd National Climate Assessment (NCA) precipitation is expected to increase over much of the United States, most significantly over the Northeast. In addition to an increase in annual precipitation accumulation, heavy precipitation events are also expected to increase in some regions (Melillo et al. 2014).

To prepare for these changes in extreme precipitation properly, the information needs to be disseminated on a local scale. The spatial scale to represent local conditions should be on the order of 10km and currently most global climate models (GCMs) produce information on the order of 100km (Pierce et al. 2014). This has created a divide between the information provided by GCMs and the information that is needed to implement adaptation strategies.

The goal of this project is to provide a tool for visualizing the projections of extreme precipitation on a local scale. The tool was created with a wide variety of uses in mind, from providing information to assist in key decision making to helping a family member understand possible impacts of climate change. Allowing city officials, like emergency managers, to relate climate information to their local region will provide better direction on things they need to do to adapt and prepare for the future. City planners and others working in infrastructure would be able to use this tool in the planning process of future roads or bridges and allow them to take into account projections of extreme precipitation for their immediate area. This tool can also be used in workshops for teaching about climate change and the possible effects it may have. People often relate best to extreme events and seeing this information about their own local areas could bring awareness to climate change. The workshops can also be held for stakeholders in these sectors that are affected by changes in precipitation where they would be taught how to use the tool.

2. Methods

a. Historical Data Source

To assess climate information, historical data are needed to provide a basis for how certain measurements have behaved over a period of record. For this project, the Global Historical Climatology Network-Daily (GHCN-D; Menne et al. 2012) dataset was utilized to calculate a historical record of extreme precipitation variables at locations across the United States.

The GHCN-D network was created to provide a historical dataset with maximum spatial coverage by using the historical daily observations of as many global observing networks as possible. Overall, GHCN-D is comprised of roughly 100,000 stations around the globe (Figure 2) and includes observations of daily minimum and maximum temperature, precipitation, and snowfall (NOAA 2018b). The process of integrating this many established observing networks is described in Menne et al. (2012) as having three steps. The first is to eliminate source data from stations whose location was questionable or unknown; then, the remaining stations are classified as either a new site or one that is already represented in GHCN-D. Finally, any previous data and the data from the new source dataset are combined into a single station record.

GHCN-D dataset offers a very dense network of data, allowing for locally relevant information to be gained. Figure 3 shows the spatial density of the GHCN-D network for various periods of record for both temperature and precipitation measurements (Data.gov 2018). The concentration of the stations in the United States included in the GHCN-D network is very dense for periods of record starting after 1890.

In the United States, the GHCN-D dataset is made up of stations from several different networks including ASOS (Automated Surface Observing System), COOP (Cooperative Observer Network), CRN (Climate Reference Network), and CoCoRaHS (Community Collaborative Rain, Hail, and Snow Network). The overall length of the historical record of weather data is dependent on the GHCN station itself. Most ASOS and COOP stations offer periods of record starting in the late 1800s or early 1900s, making these good candidates for analyzing climate metrics. ASOS stations were developed in a partnership between the National Weather Service (NWS) and the Federal Aviation Administration (FAA) and there are now over 900 stations in the United States located at many airports and NWS sites (All Weather Inc. 2014). COOP stations offer daily data recorded by volunteers from roughly 10,000 sites all over the United States (NOAA, n.d.). Since the ASOS and COOP stations typically have long records and are well maintained, they were chosen to be used for this project.

b. Quality Assurance

The GHCN-D network undergoes thorough quality assurance checks on a regular basis. Prior to becoming a GHCN-D station, certain standards must be met in order to qualify as a valid observing station. The first of the standards is that the station must have valid metadata meaning that the station name, latitude, and longitude must be identified. The station must also provide at least 100 daily values for at least one of the five main GHCN-D measurements (minimum temperature, maximum temperature, precipitation, snowfall, or snow depth). Finally, the station data are checked with existing GHCN-D station data; if more than 50% of the data are identical to another dataset the station with the longer record is kept (Menne et al. 2012). Once the site is an official GHCN-D station, automated quality assurance checks are performed. These include format checking, data value quality tests, and a manual review of any flagged data. The QA tests also check the integrity of the record by making sure that climatological means are consistent with station location, there are no large jumps in annual means, and there are no groups of values that fail the automated QA tests mentioned above.

While the rigorous quality assurance procedures ensure trustworthy GHCN-D data, further steps were taken to ensure that good data were chosen for the extreme precipitation visualizations in this project. To ensure the validity of the data chosen, the stations used are ones that had at least 50 years of data, at least 50% availability during the overall period of record, and at least 90% availability during 1981-2010 normals. After these criteria were applied, around 3500 ASOS and COOP stations throughout the conterminous United States were included in the project (Figure 4).

c. Precipitation Indices

The historical data from GHCN-D were used to calculate several extreme precipitation indices. These indices (Karl et al. 1999, Peterson et al. 2001), developed in part by the World Meteorological Organization (WMO), include annual accumulation percentiles, annual 1-day and 5-day maximum daily precipitation, and annual consecutive wet and dry days. For this application, the percentile variables used include the days when precipitation is above the 99th percentile as well as the annual accumulation above the 99th percentile for the 1981-2010 period of normals. The percentile is calculated by ordering the historical annual accumulation of precipitation from least to greatest and finding the value that corresponds to the 99th percent. For each year in the historical record of each station, the number of days in which the precipitation accumulation surpasses this 99th percentile value is counted. Table 1 provides the specifics of the variable calculations from the WMO.

d. Climate projections

The historical data from GHCN-D were projected out to the year 2100 using a 29-member ensemble of Localized Constructed Analogs (LOCA; Pierce et al. 2014). LOCA is a statistical downscaled version of climate model simulations of daily temperature and precipitation. The goal of the LOCA dataset is to provide climate model data at an appropriate spatial scale for making climate adaptation decisions. The resulting dataset is gridded on a 1/16-degree latitude-longitude grid; this equates to a spatial scale of about 7km.

The LOCA data used in this project are a 29-member ensemble of the climate data for two different representative concentration pathways (RCPs) representing different climate scenarios. One of the scenarios, RCP 4.5, is representative of techniques for reducing greenhouse gas emissions being applied by 2100 to stabilize the total radiative forcings (Clarke et al. 2007). The other scenario, RCP 8.5, represents an increase in greenhouse gas emissions over time leading to overall high greenhouse gas concentration levels (Riahi et al. 2007).

The observed training data used to develop LOCA were provided by Livneh et al (2013). The Livneh et al (2013) data, gridded to the same 1/16th degree grid as LOCA, are a long-term hydrologically based dataset. This dataset derives gridded data from precipitation and daily minimum and maximum temperature observations that were collected from COOP stations over the United States. To ensure that GHCN-D data were valid to use as a historical dataset along with the projections of LOCA, the extreme precipitation metrics calculated with GHCN-D data were compared to that of Livneh et al. (2013). Sites from each of the NCA regions (Figure 5) over the conterminous United States were used to show the comparison of the two datasets. The Pearson correlation coefficient was computed for each station to show the relation between the Livneh et al. (2013) and GHCN-D data. For both precipitation metrics, all stations produced Pearson values very near to 1.0 (perfect correlation). The results show that the Livneh et al. (2013) and GHCN-D data are positively correlated and validates the use of GHCN-D and LOCA data (Figures 6 and 7). The high resolution allowed for the GHCN-D stations to be matched to the nearest LOCA grid point for projection of future climate and still be relevant on a local scale.

e. *Story Map Application*

There are many tools currently in use for examining climate data. NOAA produces numerous charts and tables that present information about how current weather conditions compare to historical observations (climate.gov). The NCA provides outlooks for regions and this information is easily accessible on the Global Change website (Global Change, 2014). However, there are few tools that offer climate information about changes that may be seen locally.

The Story Map function is a customizable way to display information, specifically, information involving map-based data. There are many applications of the Story Map, for example, you can find Story Maps that provide information on storm surge risk, historical houses in Brooklyn Park, and the United States national trail system. There is a gallery on their website of Story Maps from numerous disciplines (https://storymaps.arcgis.com/en/gallery/#s=0). As can be inferred from the name, the overall purpose of the Story Map feature is to tell a story using visual information that is easy to understand and use by the general public.

Since there are so many uses for the Story Maps, ESRi has made the creation of the websites very customizable. Many preset options are available and creating the story is a matter of selecting how the information should be displayed and including the relevant text. For the data visualization portion of this project, the data were calculated and written into a CSV file which was then uploaded into ArcOnline and visualized to create an interactive map. The map shows the current values for each metric and what the values are projected to be by the end of the century using the RCP 8.5 ensemble.

f. Story Map Walkthrough (https://arcg.is/0qmaf8)

To begin, the map starts with an introduction discussing extreme precipitation and the value of seeing the extremes on a local scale. The user can then scroll down to get information on GHCN-D data and LOCA. It features the figures showing the relationship between the Livneh et al. (2013) and GHCN-D historical data in validating the use of LOCA for the climate projections.

As the user scrolls farther down, the interactive map displaying the data comes up along with a sidebar that explains the variable being shown, data color bars, and a brief analysis of what the data are showing (Figure 9). One of the Story Map features includes a slide bar to show the difference between two images. This feature is utilized in showing the differences between extreme precipitation values for 2016 and 2100.

The interactive map shows historical data from 2016 on the left of the slide bar and projected data from the RCP 8.5 ensemble for 2100 on the right of the slide bar. The user can drag the slide bar on the screen to see the difference between the 2016 and 2100 data. The year 2016 was chosen because at the time of the project this was the latest dataset that had a full year of data, and 2100 was chosen to give a sense of the trend in extreme precipitation variables. In the future, the tool would benefit from showing decadal averages as the historical comparison to eliminate any bias from yearly anomalies.

The user can zoom in and out of the map to view the desired spatial scale. To get specific local information, the user can select any of the stations to activate a pop-up containing information on the station for the variable the map is currently showing (Figure 10). The pop up includes exact values of the variable for the specific station and when the user drags the bar past the station, they can examine the change in the exact value from 2016 to 2100 or vice versa (Figure 11). The time series graph shows the historical (GHCN-D) data with a black line, and the projected climate model data in the red (RCP 8.5) and blue (RCP 4.5). This graph itself can be selected to bring up a full screen version of the time series plot (Figure 12).

3. Results

The Story Map tool easily visualizes the extreme precipitation projections on a local scale; however, to ensure that the data make sense, the general analysis of the regions is compared to the projections provided by the NCA (Melillio et al. 2014). One section of the report addresses the projections of precipitation in the United States:

> The northern U.S. is projected to experience more precipitation in the winter and spring (except for the Northwest in the spring), while the Southwest is projected to experience less, particularly in the spring. The contrast between wet and dry areas will increase both in the U.S. and globally – in other words, the wet areas will get wetter and the dry areas will get drier. As discussed in the next section, there has been an increase in the amount of precipitation falling in heavy events, and this is projected to continue. (Melillo et al. 2014)

While this project doesn't consider the seasons, the general trend that the assessment describes projects more precipitation for the northern United States (the northeastern portion in particular) and less precipitation for the southern United States. The report provides an image showing the projected changes in annual precipitation and consecutive dry days under RCP 2.6 and RCP 8.5 scenarios (Figure 13). Since the visualization tool produced in this project displays RCP 8.5 projections, comparisons between the tool and the NCA figure will take into account only the RCP 8.5 projection.

The following is an analysis of each of the precipitation metrics that were analyzed for the visualization tool and how the values calculated for 2016 using historical GHCN-D data compare to the projected values for 2100. The projected values that the visualization tool shows represent the ensemble of the RCP 8.5 climate model data. The results are also compared to the NCA regional precipitation projections.

a. Days with Precipitation Above the 99th Percentile

The number of days in a year where the precipitation is above the 99th percentile can be described as a metric that shows the number of days in a year that experienced extreme precipitation. On average, it would be expected that 3-4 days would exceed the 99th percentile. Figure 14 shows the difference between the number of days with extreme precipitation between the historical data from 2016 (left) and the projected number of days with extreme precipitation for 2100 (right). It's clear that 2100 exhibits more days of extreme precipitation over the entire United States. The Eastern portion of the United States sees a significant increase in extreme precipitation days with nearly all of this region projected to see over 6 days of precipitation above the 99th percentile. The Pacific Northwest also exhibits this increase in extreme precipitation days. This aligns with the NCA projections that show an increase in precipitation for the Northeast and Pacific Northwest, however, the projections may exhibit more change in the rest of the United States than the NCA projects.

b. Annual Accumulation of Precipitation Above the 99th Percentile

Adding up the precipitation values from all of the days in a year when the precipitation is extreme gives us another way to describe the next metric. Comparing the annual accumulation of extreme precipitation for 2016 (Figure 15, left) and the projected annual accumulation of extreme precipitation for 2100 (Figure 15, right) shows a clear increase in extreme precipitation accumulation in much of the Eastern United States, which follows what was observed in the number of days with extreme precipitation. However, this metric shows more extreme rain accumulating in the southeastern portion of the United States. Where the number of days with extreme precipitation increased over the entire United States, the accumulation of extreme precipitation doesn't increase for much of the western half of the United States, apart from the increase in the coastal areas in the West. Similar to the annual number of days with precipitation above the 99th percentile, the annual precipitation accumulation projection follows the NCA predictions. Comparing the current results to the NCA projections for the percent change in annual accumulation, the greatest change in annual accumulation occurs in similar regions. It should be noted, however, that the visualization for the 2016 annual accumulation is affected by Hurricane Matthew, which made landfall along the coasts of South Carolina and North Carolina (Figure 16).

c. Maximum 1-day Precipitation

The maximum 1-day precipitation in the visualization tool shows the maximum daily precipitation that was seen by each station in the year 2016 and the projected maximum daily precipitation value for each station in 2100 (Figure 17). The New England area is projected to see a slight increase in the maximum 1-day precipitation amounts. However, much of the United States does not show much change, if not a decrease, in the maximum 1-day precipitation amounts. This could be due to the fact that the projected values for 2100 are an ensemble, or average, of the various models. This could take away some of the more extreme values that may have otherwise shown up.

d. Maximum 5-day Precipitation Accumulation

Similar to the 1-day precipitation maximum, the 5-day precipitation maximum is the largest sum of the precipitation amounts for a 5-day interval for each station in the year 2016 and the projected accumulation of the wettest 5-day interval for 2100 (Figure 18). Some of the eastern United States is expected to see an increase in the maximum 5-day precipitation amounts and the West Coast is expected to see high amounts of 5-day precipitation accumulation. As with the 1-day precipitation maximum, the projected values for 2100 could be dampened by the averaging of the climate models.

e. Maximum Consecutive Wet Days

The maximum consecutive wet days are depicted in the visualization tool comparing the number of consecutive days for each station where precipitation was greater than 1mm in 2016 and the projected value of the metric for 2100 (Figure 19). Most of the eastern half of the United States sees an increase in consecutive wet days along with some areas of the West Coast. There is a small increase in wet days in areas of the Southwest such as parts of Arizona and New Mexico.

f. Maximum Consecutive Dry Days

Calculated the same way as the maximum consecutive wet days, the maximum consecutive dry days for the year 2016 is compared to the projected consecutive dry days for 2100 (Figure 20). The observations seen in the visualization tool are consistent with the observations from the wet day visualization; the eastern half of the United States, which exhibited an increase in consecutive wet days, doesn't see an increase in consecutive dry days. The Southeast shows a dramatic decrease in consecutive dry days which could be attributed to the drought that occurred in the Southeast in the later part of 2016 (Figure 21). In the west, many of the stations are projected to see an increase in consecutive dry days. The Pacific Northwest in particular is expected to see a significant increase in dry days, especially in the traditionally dry portions of Oregon and

Washington. The increase in consecutive dry days follows the projections addressed in the NCA. Compared to the projected dry days using RCP 8.5, the greatest change in consecutive dry days occurs in the Southwest and Pacific Northwest regions for both the NCA projections and the visualization tool.

4. Summary and Conclusions

The Story Map visualization tool for extreme precipitation aims to provide easy to understand information about the implications of a changing climate and what changes may take place in a local region. The results match the projections of the NCA: much of the eastern half of the United States can expect increases in extreme precipitation, and portions of the western United States are projected to see an increase in consecutive dry days. While these regional projections are already available from the NCA report, the tool provides locally relevant information that can help inform decisions for adaptation to climate change on a smaller scale.

Future steps for the project would include using decadal averages or metrics calculated for decade long periods rather than the single year historical data. This would provide more useful comparisons to the future projections. It would also be useful to add other indices to the tool such as temperature extremes or heating and cooling days. These indices would provide key information to those that are interested in future energy use.

Figures

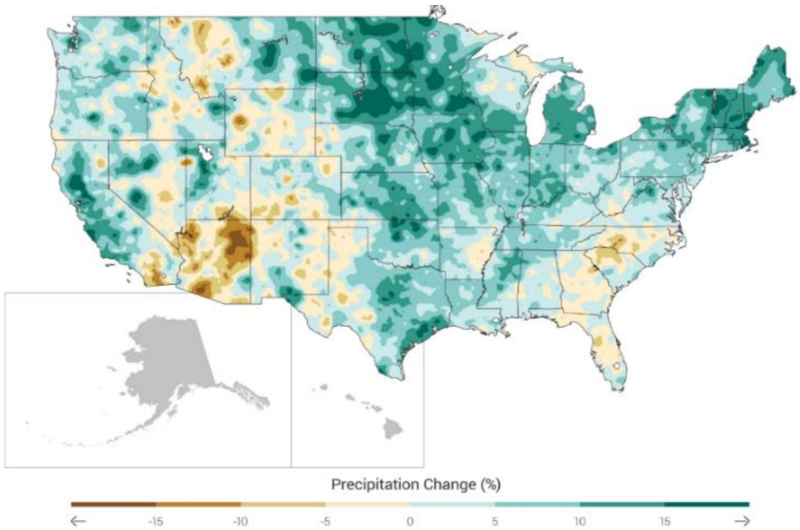


Figure 1 Annual total precipitation changes for 1991-2012 compared to the 1901-1960 average (Source: adapted from Peterson et al. 2013).

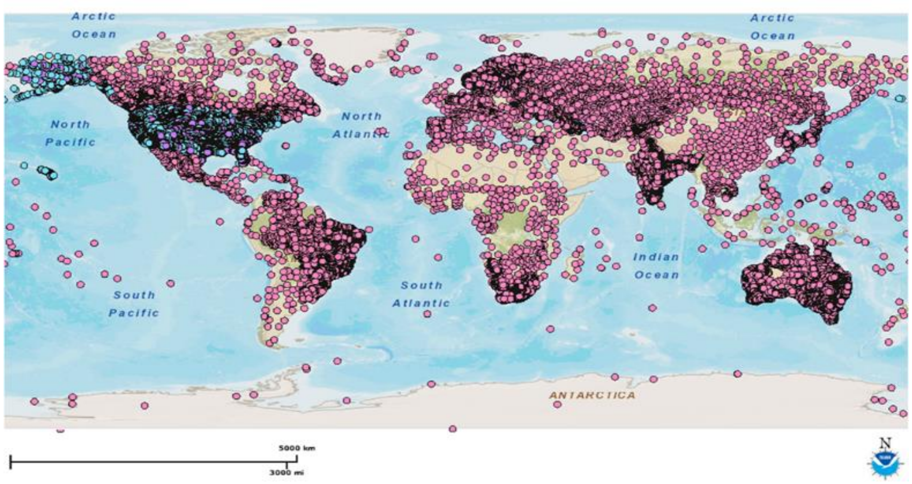


Figure 2 Global Historical Climatology Network station locations. (Source: data.gov 2018)

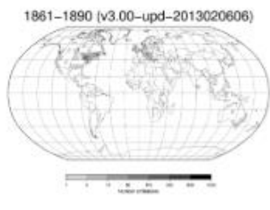
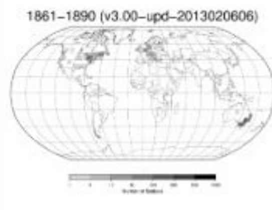
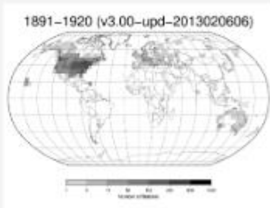
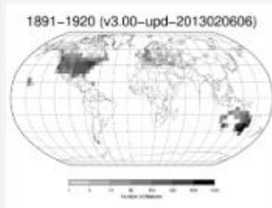
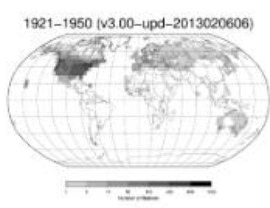
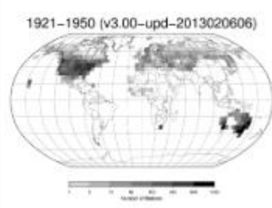
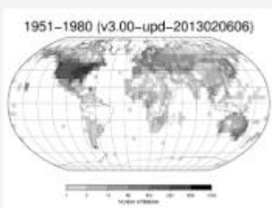
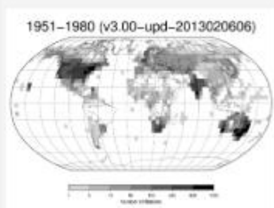
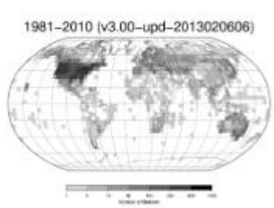
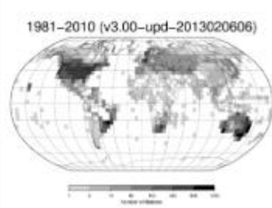
Years	Temperature	Precipitation
1861 - 1890		
1891 - 1920		
1921 - 1950		
1951 - 1980		
1981 - 2010		

Figure 3 Density of GHCN-D stations that have at least 10 years of precipitation or temperature records for the given time interval. (Source: NOAA 2018b)

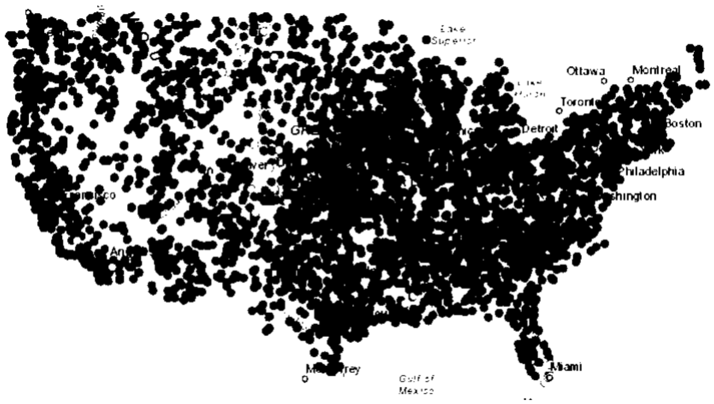


Figure 4 Stations (ASOS and COOP) used in the project for extreme precipitation visualization.

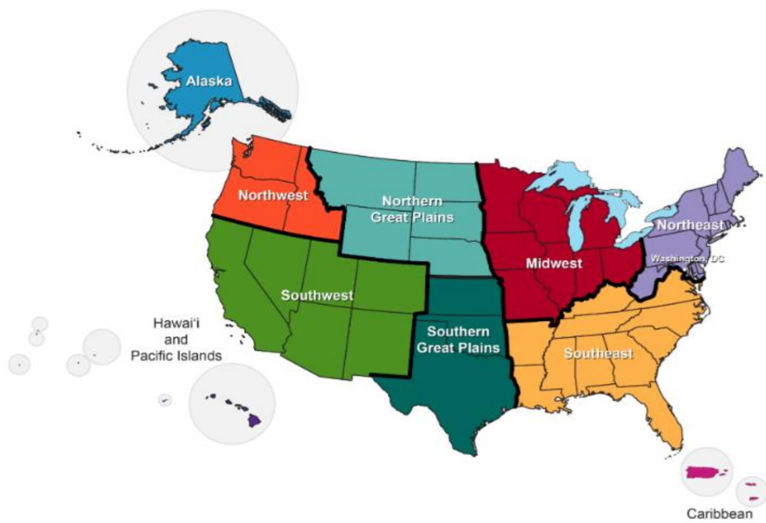


Figure 5 National Climate Assessment regions in the United States. (Source: Global Change, n.d.)

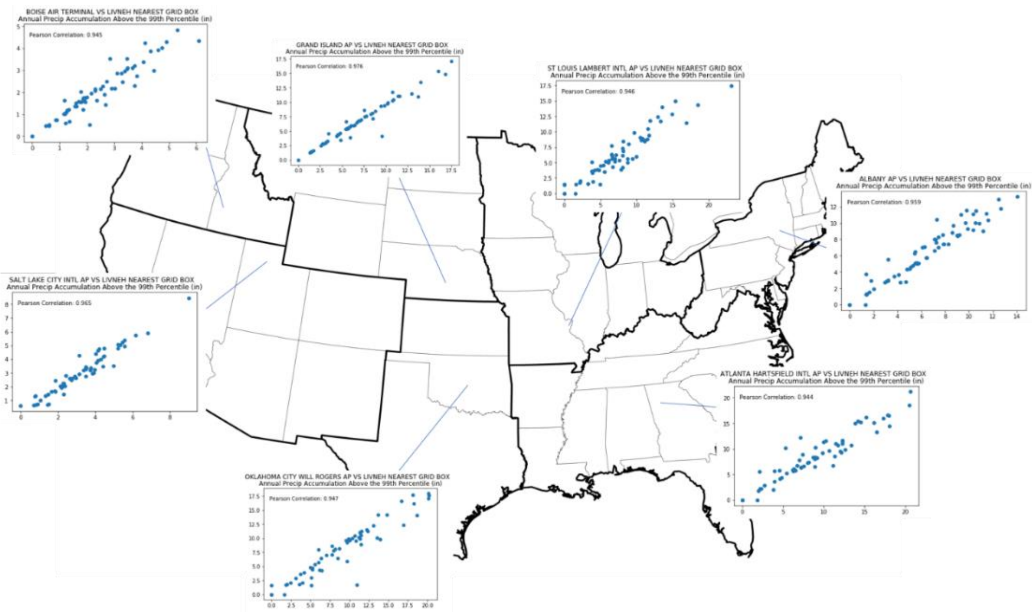


Figure 6 Scatter plots of annual precipitation accumulation above the 99th percentile values from GHCN-D and Livneh et al. (2013) for a station in each NCA region.

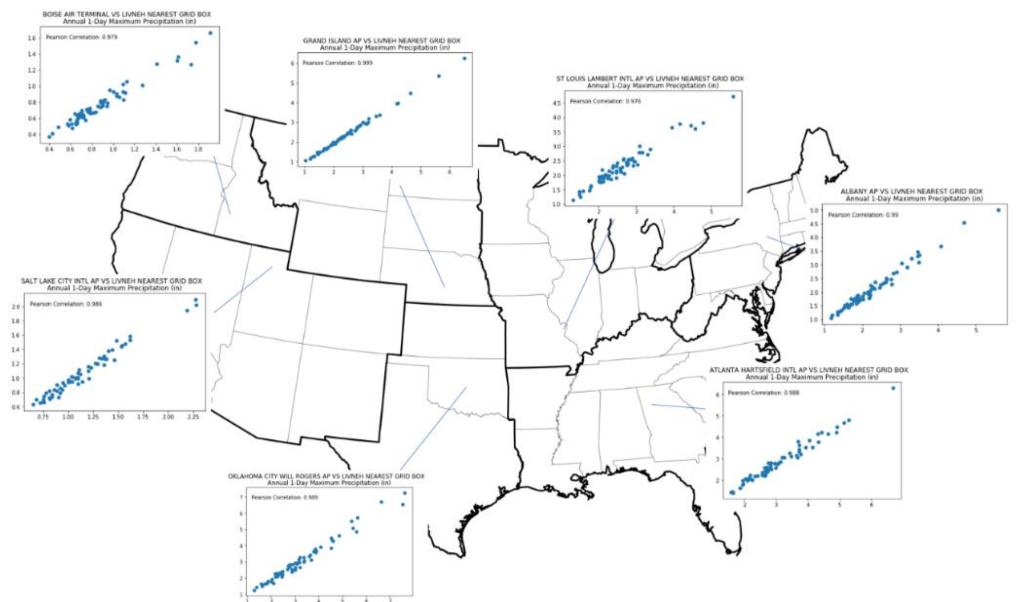


Figure 7 Scatter plots of one day maximum precipitation accumulation values from GHCN-D and Livneh et al. (2013) for a station in each NCA region.

Figure 8 Story Map title page

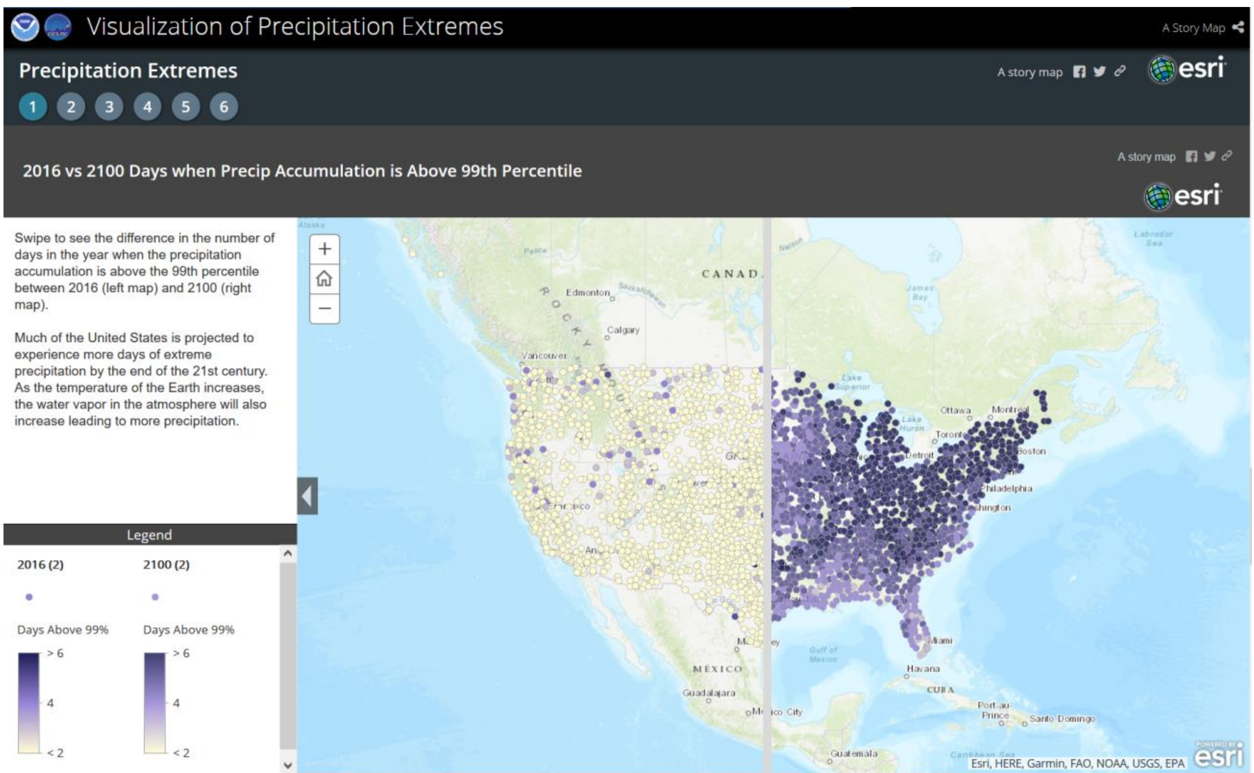


Figure 9 Screenshot of the interactive map application. Description and legend on the left-hand side. Slide bar in the middle which can be dragged to show the data values from 2016 (left) to 2100 (right). Numbers at the top can be selected to change the data from one index to another.

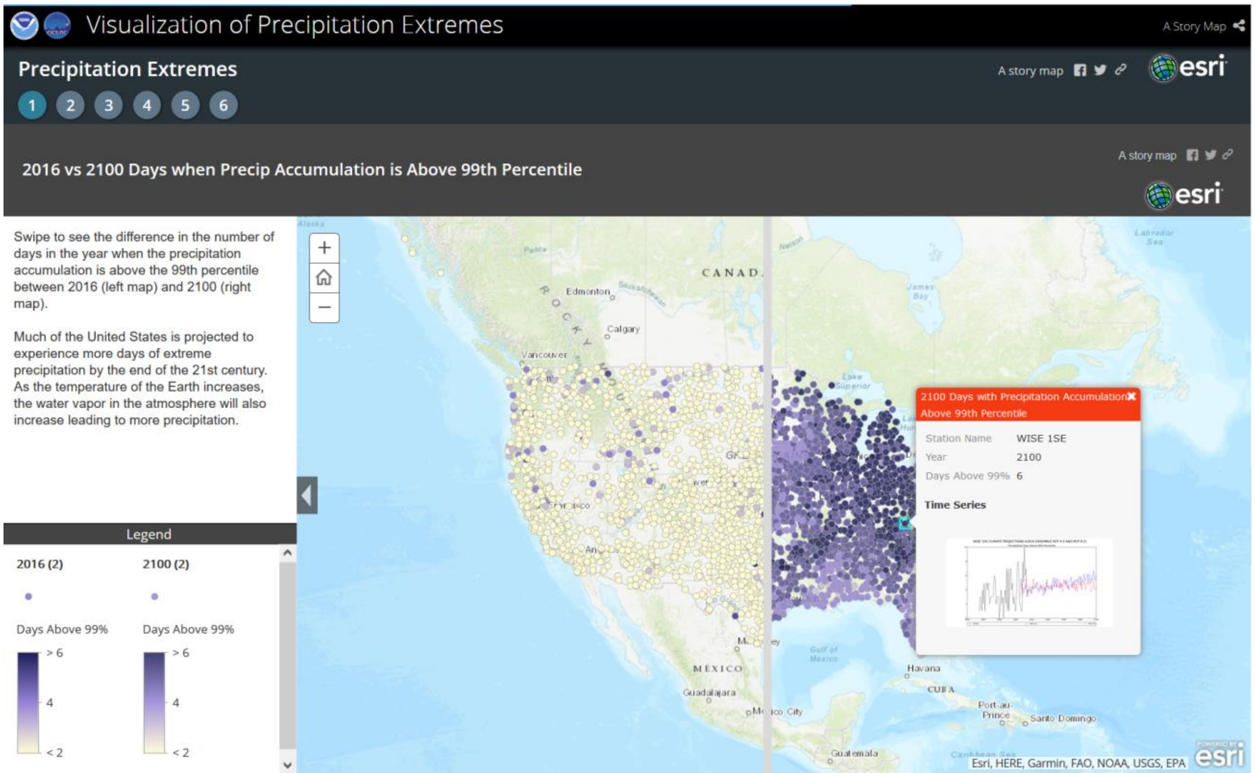


Figure 10 Screenshot of the interactive map application. Demonstrates the user selecting a single station and the pop up that appears. Within the popup the station name is included, along with the data value for the extreme precipitation metric and the year. In the lower portion of the pop up, a time series of the data appears.

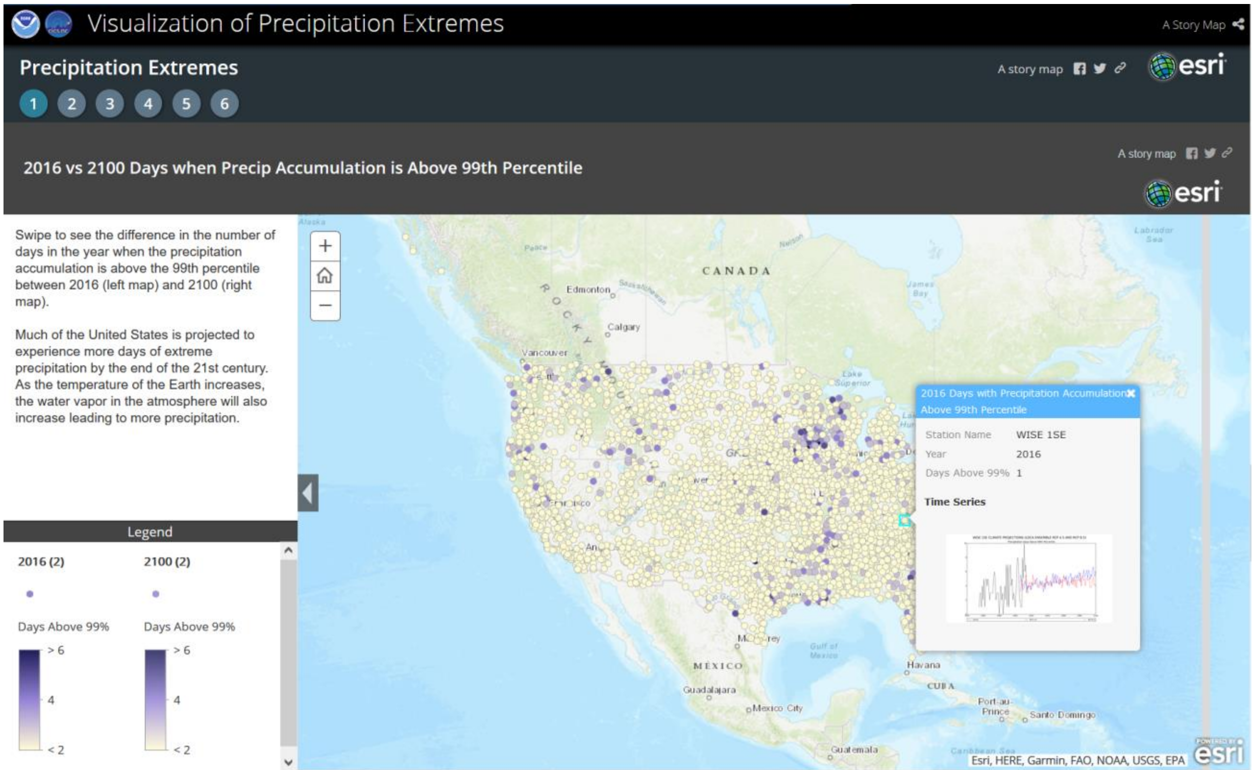


Figure 11 Screenshot of the interactive map application. Demonstrates the ability to move the slide bar while the pop up is displayed and the value/year changes as well.

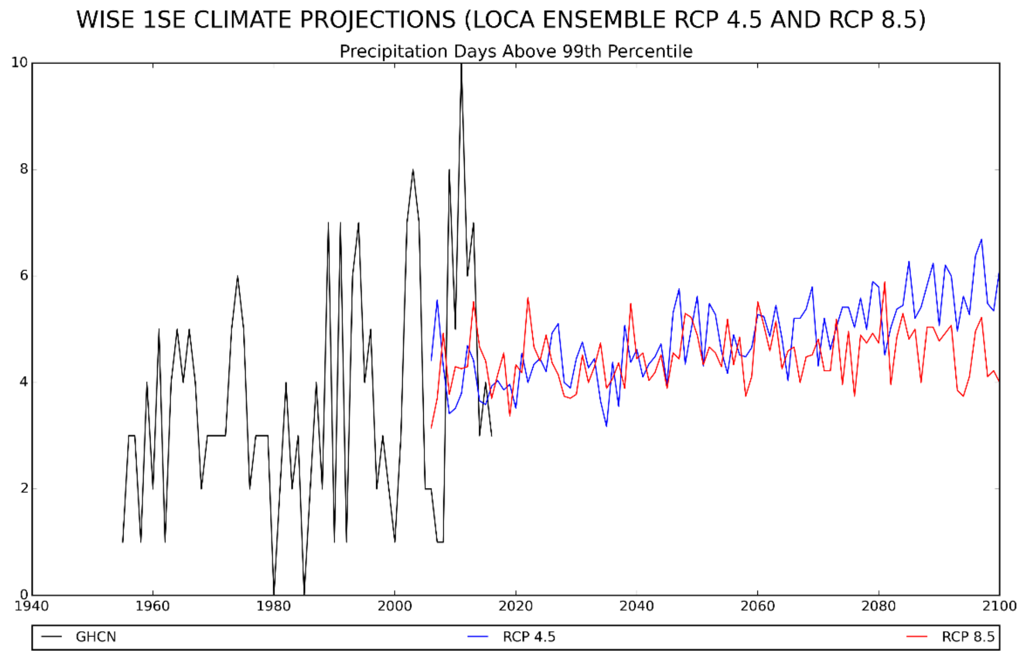


Figure 12 Time series of the extreme precipitation variable. Historical data (black) compared to the climate model data RCP 4.5 (blue) and RCP 8.5 (red).

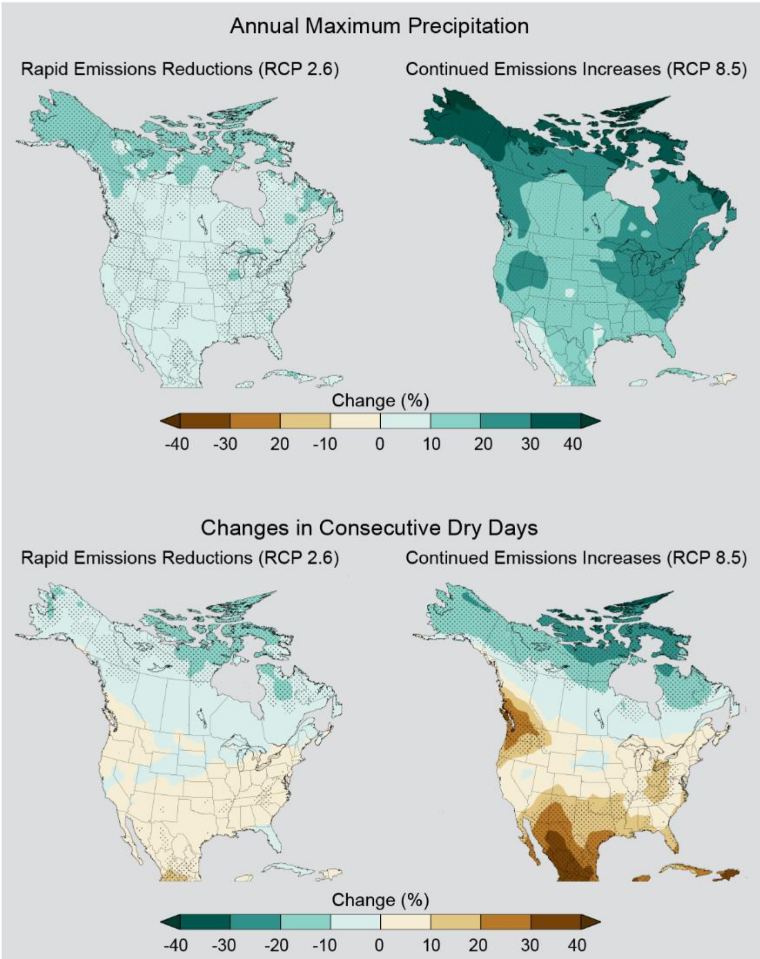
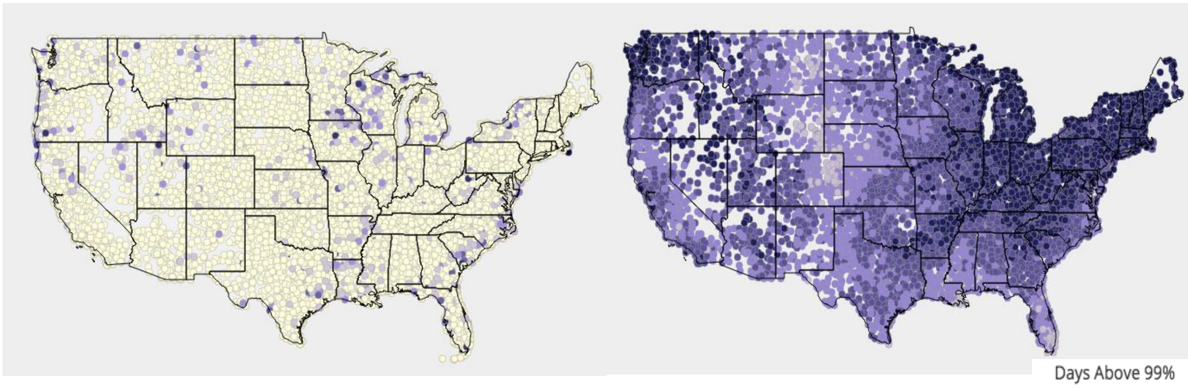


Figure 13 From the NCA. Projections of change in annual precipitation and consecutive dry days. RCP 2.6 scenario represented by the maps on the left and RCP 8.5 scenario on the right. (Source: Global Change, 2014)



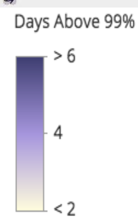
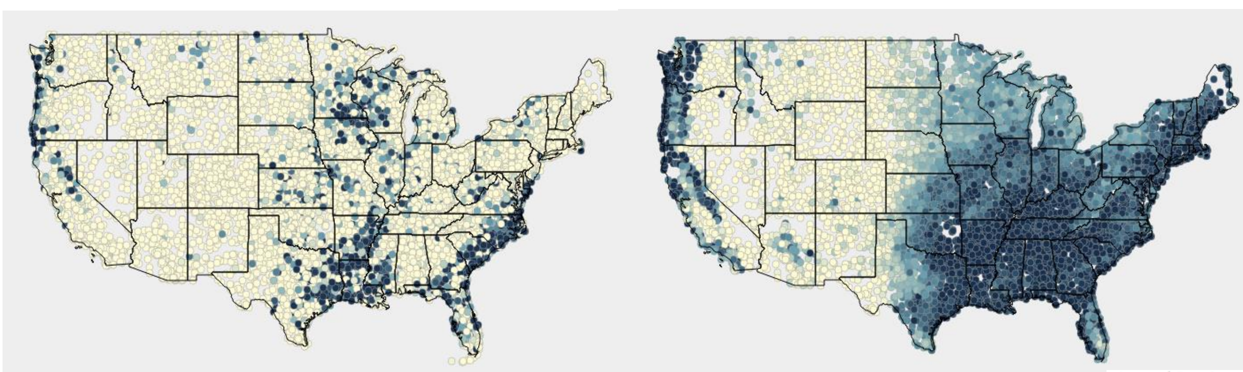


Figure 14. Number of days when precipitation is above the 99th percentile for 2016 (left) and climate projection for 2100 using climate models RCP 8.5 (right)



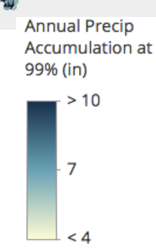


Figure 15 Annual precipitation accumulation above the 99th percentile for 2016 (left) and climate projection for 2100 using climate models RCP 8.5 (right)

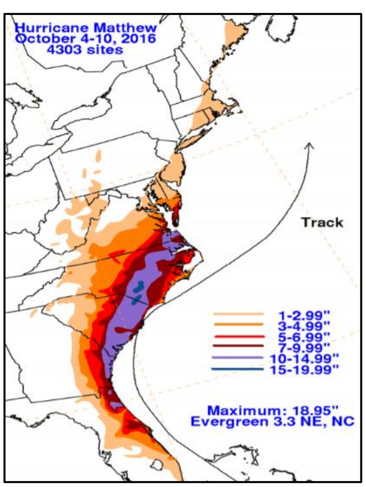
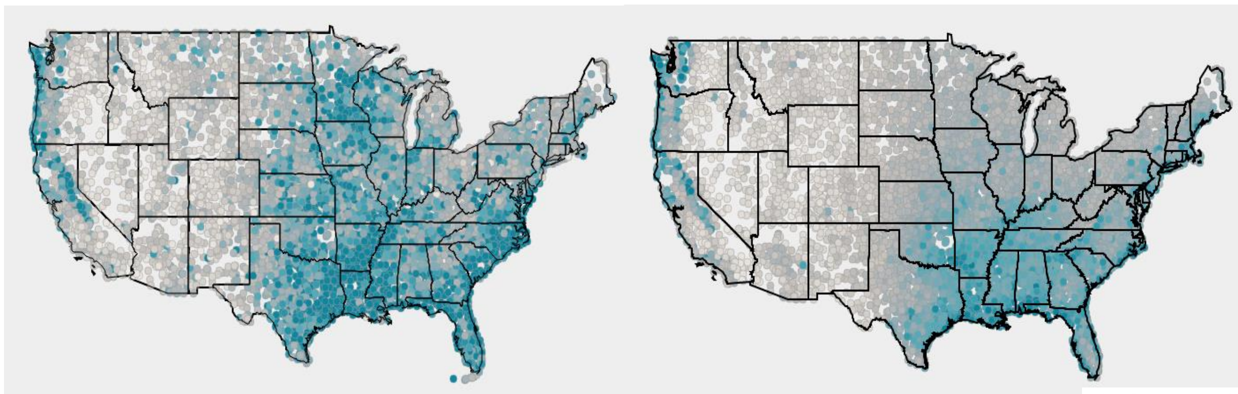


Figure 16 Total precipitation accumulation from hurricane Matthew. The figure comes from the National Hurricane Center report on hurricane Matthew (Source: Stewart, 2017).



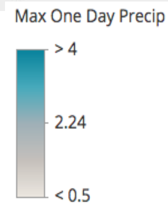
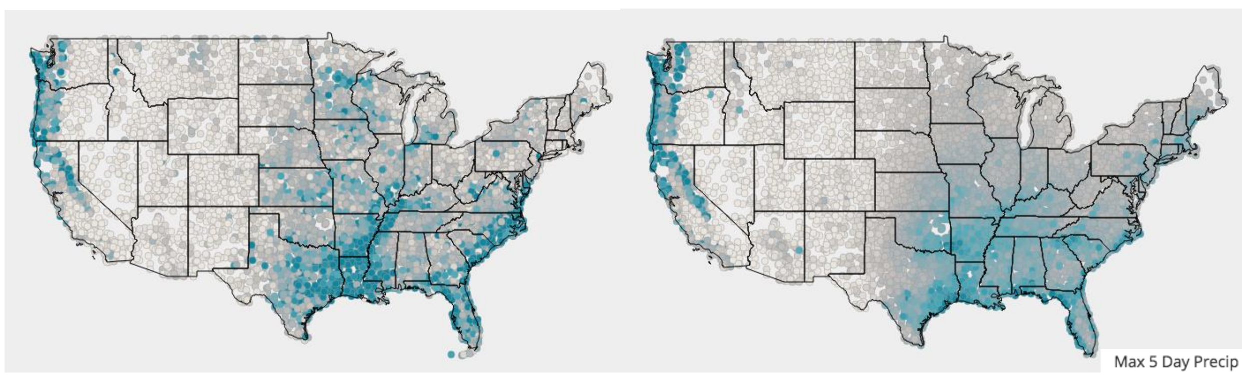


Figure 17 Maximum 1-day precipitation accumulation for 2016 (left) and climate projection for 2100 using climate models RCP 8.5 (right)



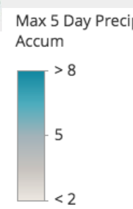
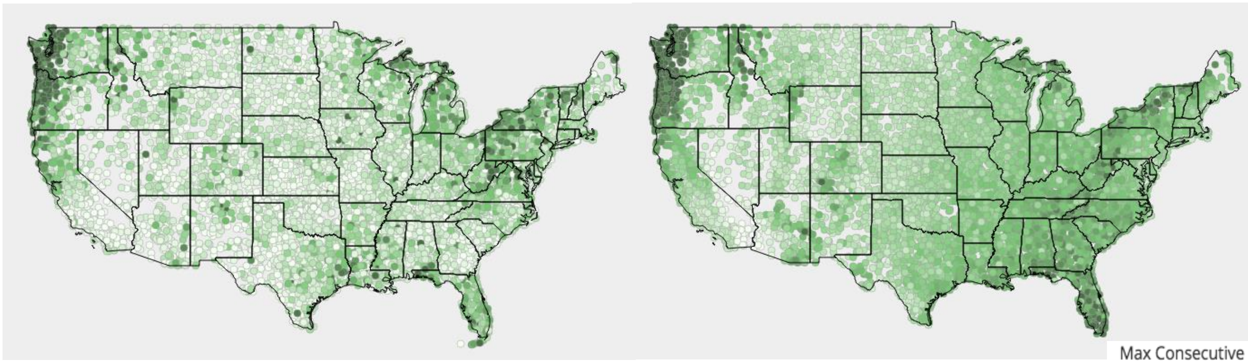


Figure 18 Maximum 5-day precipitation accumulation for 2016 (left) and climate projection for 2100 using climate models RCP 8.5 (right)



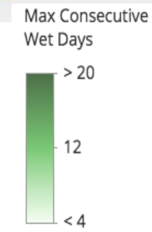
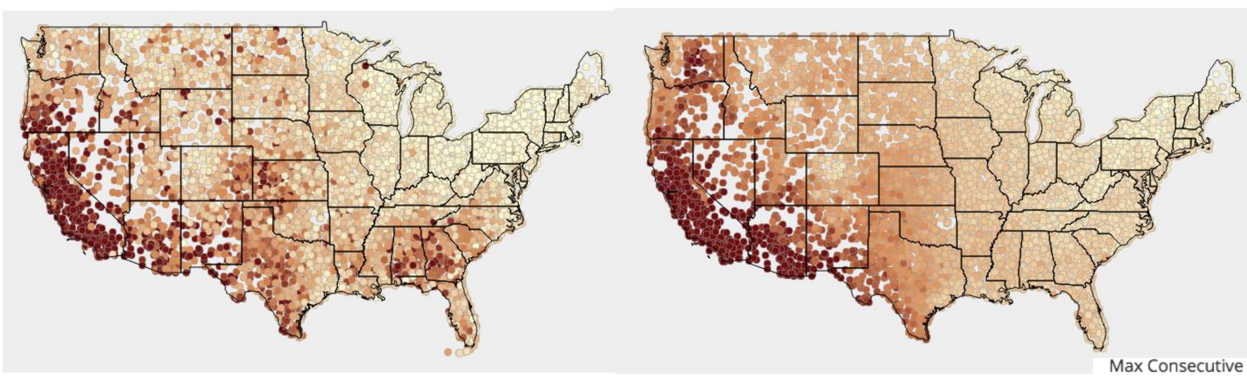


Figure 19 Maximum consecutive wet days for 2016 (left) and climate projection for 2100 using climate models RCP 8.5 (right)
)



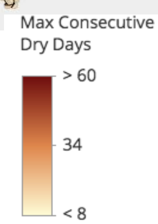
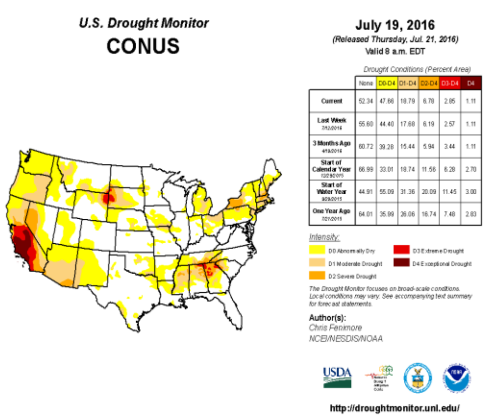


Figure 20 Maximum consecutive dry days for 2016 (left) and climate projection for 2100 using climate models RCP 8.5 (right)



	None	D0-D4	D1-D4	D2-D4	D3-D4	D4
Current	52.34	47.66	18.79	6.78	2.85	1.11
Last Week	55.60	44.40	17.68	6.19	2.57	1.11
3 Months Ago	60.72	39.28	15.44	5.94	3.44	1.11
Start of Calendar Year	66.99	33.01	18.74	11.56	6.28	2.70
Start of Water Year	44.91	55.09	31.36	20.09	11.45	3.00
One Year Ago	64.01	35.99	26.06	16.74	7.48	2.83

Figure 21 US Drought Monitor from July 19, 2016 beginning to show dryness in the Southeast. (Source: USDM)

Tables

Table 1: Selected WMO climate indicies for precipitation		
R99pTOT	Annual total PRCP when RR > 99p: RRwj = daily precipitation amount on a wet day w (RR ≥ 1.0mm) in period i and let RRwn99 be the 99th percentile of precipitation on wet days in the 1981-2010 period. W represents the number of wet days	$R99p_j = \sum_{w=1}^{W} RR_{wj}$ where $RR_{wj} > RR_{wn}99$
$Rx1day_j$	Maximum one day precipitation in period j	$Rx1day_j = \max(RR_{ij})$
$Rx5day_j$	Maximum precipitation in period j for the 5-day interval ending in k	$Rx5day_j = \max(RR_{kj})$
CWD	Maximum length of consecutive days with RR ≥ 1mm	*Largest consecutive days where:* $RR_{ij} \geq 1mm$
CDD	Maximum length of consecutive days with RR < 1mm	*Largest consecutive days where:* $RR_{ij} < 1mm$

REFERENCES

All Weather Inc., 2014: FAA ASOS. Accessed 14 October 2018, http://www.allweatherinc.com/programs/faa-asos/.

Clarke, L., J. Edmonds, H. Jacoby, H. Pitcher, J. Reilly, R. Richels, 2007. Scenarios of Greenhouse Gas Emissions and Atmospheric Concentrations. Sub-report 2.1A of Synthesis and Assessment Product 2.1 by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research. Department of Energy, Office of Biological & Environmental Research, Washington, 7 DC., USA, 154 pp.

Data.gov, 2018: Global Historical Climatology Network - Daily (GHCN-Daily), Version 3. Accessed 14 October 2018, https://catalog.data.gov/dataset/global-historical-climatology-network-daily-ghcn-daily-version-3

Global Change, 2014: National Climate Assessment. Accessed 14 October 2018, https://nca2014.globalchange.gov/

Global Change, n.d.: Regions. Accessed 14 October 2018, https://scenarios.globalchange.gov/regions_nca4

Karl, T.R., N. Nicholls, and A. Ghazi, 1999: CLIVAR/GCOS/WMO workshop on indices and indicators for climate extremes: Workshop summary. *Climatic Change*, 42, 3-7.

Livneh, B., E. A. Rosenberg, C. Lin, B. Nijssen, V. Mishra, K. Andreadis, E. P. Maurer, and D. P. Lettenmaier, 2013: A long term hydrologically based dataset of land surface fluxes and states for the conterminous United States: Updates and extensions. *J. Climate*, **26**, 9384–9392, doi:10.1175/JCLI-D-12-00508.1

Melillo, J. M., T. C. Richmond, and G. W. Yohe, Eds., 2014: *Climate Change Impacts in the United States: The Third National Climate Assessment*. U.S. Global Change Research Program, 841 pp., doi:10.7930 /J0Z31WJ2.

Menne, M. J., I. Durre, R. S. Vose, B. E. Gleason, and T. G. Houston, 2012: An overview of the Global Historical Climatology Network-Daily Database. *J. Atmos. Oceanic Tech.*, **29**, 897–910, doi:10.1175 /JTECH-D-11-00103.1.

NOAA National Centers for Environmental Information (NCEI), 2018a: U.S. Billion-Dollar Weather and Climate Disasters. Accessed 11 October 2018, https://www.ncdc.noaa.gov/billions/

NOAA National Centers for Environmental Information (NCEI), 2018b: Global Historical Climate Network Daily – Description. Accessed 14 October 2018, https://www.ncdc.noaa.gov/ghcn-daily-description

NOAA National Centers for Environmental Information (NCEI), n.d.: Cooperative Observer Network (COOP). Accessed 14 October 2018, https://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/cooperative-observer-network-coop

Parry, M. L., O. F. Canziani, J. P. Palutikof, P. J. van der Linden, and C. E. Hanson, Eds., 2007: *Climate Change 2007: Impacts, Adaptation, and Vulnerability.* Cambridge University Press, 976 pp.

Peterson, T.C., and Coauthors: Report on the Activities of the Working Group on Climate Change Detection and Related Rapporteurs 1998-2001. WMO, Rep. WCDMP-47, WMO-TD 1071, Geneve, Switzerland, 143pp.

Pierce, D.W., D.R. Cayan, and B.L. Thrasher, 2014: Statistical Downscaling Using Localized Constructed Analogs (LOCA). *J. Hydrometeor.*, **15**, 2558–2585, https://doi.org/10.1175/JHM-D-14-0082.1

Riahi, K., Rao, S., Krey, V. et al. Climatic Change (2011) 109: 33. https://doi.org/10.1007/s10584-011-0149-y

Stewart, S. R., 2017: Hurricane Matthew: 99. https://www.nhc.noaa.gov/data/tcr/AL142016_Matthew.pdf