

FINAL REPORT

Linked Rainfall and Runoff Intensity-Duration-Frequency in the Face of Climate Change and Uncertainty

SERDP Project RC-2514

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Yonas Demissie
Washington State University

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LIST OF ACRONYMS

AFB	Air Force Base
AMO	Atlantic Multidecadal Oscillation
AMS	Annual maximum precipitation time series
BMA	Bayesian Model Averaging
CMIP5	Coupled Model Intercomparison Project Phase 5
CONUS	Contiguous United States
DoD	Department of Defense
DSI-3240	U.S. Hourly Precipitation Data
DSI-3260	U.S. 15 Minute Precipitation Data
DSI-3505	Integrated Surface Global Hourly Data
EQCDF	Equiratio CDF Matching
EQMM	Equidistance Quantile Matching
FCM	Fuzzy C-Means
GCM	General Circulation Model
GEV	Generalized extreme value
GHCN	Global Historical Climatology Network
GIS	Geographic Information System
GLO	Generalized logistic
GNO	Generalized normal
GP	Generalized Pareto
GSOD	Global Summary of the Day
HEC-HMS	Hydrologic Engineering Center – Hydrologic Modeling System
IDF	Intensity-Duration-Frequency
MCMC	Markov Chain Monte Carlo
MEI	Multivariate ENSO Index
NAO	North Atlantic Oscillation
NCDC	National Climatic Data Center
NERSC	National Energy Research Scientific Computing Center
NINO	ENSO Index
NWS	National Weather Service
PDO	Pacific Decadal Oscillation
PE3	Pearson type-3

PG	Proving Ground
PNA	Pacific/North American
RCM	Regional Climate Model
RCP8.5	Representative Concentration Pathways 8.5
SDM	Scaled Distribution Mapping
SERDP	Strategic Environmental Research and Development Program
SMA	Soil Moisture Accounting
SOI	Southern Oscillation Index
SWMM	Storm Water Management Model
UEB	Utah Energy Balance
WRF	Weather Research and Forecasting

KEYWORDS

IDF Curves

Extreme Precipitations

Trends Precipitations

Runoff and Floods

Snowmelt

Frequency Analysis

Bayesian Approach

Uncertainty

Climate Model Projections

Dynamic Downscale

Bias Correction

Web-GIS

Intensity-Duration-Frequency

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1. ABSTRACT

Introduction and Objectives: The Department of Defense (DoD) recognizes the effects of climate change as a growing national security threat with potential impacts on critical military installations and operations. One of the anticipated effects of climate change is the increase in intensity and frequency of extreme precipitation and subsequent flood events. Adaptation to this change requires proper design and management of stormwater facilities using improved and updated characterization of the intensity-duration-frequency (IDF) of storms. The primary objective of this project is to revise and update storm and flood IDF relationships (or curves) for selected military installations by considering changes in the past and future storm and flood events, effect of snowmelt, and modeling and data uncertainties. Regional frequency analysis coupled with Bayesian uncertainty quantification were used to update rainfall IDF curves, which are then used by site-specific hydrologic models to develop runoff IDF curves that can be used to assess the vulnerability of military installations to flooding. The resulting rainfall and runoff IDF curves provide reliable, forward-looking, and spatially resolved characteristics of storm events and flooding risks for thorough review and update of the current stormwater design standards at the selected installations. An interactive web-based geographic information system (GIS) interface was developed, which contains tabulated and geo-referenced IDF data and figures.

Technical Approach: The IDF curves – describing the probabilistic relationship between rainfall intensity, duration, and frequency (return period) – are commonly used for designing and managing hydrologic and hydraulic infrastructures. This project utilized statistical and modeling approaches to develop rainfall and runoff IDF curves that consider the potential changes in extreme precipitation and watershed, effects of snow on both extreme precipitation and runoff, modeling, and data uncertainties. A new framework was developed using (1) a modified L-moment algorithm to regionalize IDF curves and improve the representation of spatial variations of rainfall for various durations, (2) a Bayesian model averaging to quantify the uncertainty in the IDF curves resulting from the selection of probability distribution models and estimation of the model parameters, (3) a dynamic downscale and bias correction approaches to generate high-resolution spatial and temporal precipitation and temperature projections, 4) a recursive Bayesian analysis algorithm to update the IDF curves using recently observed and projected extreme precipitation, (5) a hydrologic, snowmelt and hydraulic models to develop the runoff IDF curves and directly assess flood risk, (6) an interactive web-based Geographic Information Systems (GIS) tool and a geo-database to facilitate construction and an update to the rainfall and runoff IDF curves for any military installation and region of interest to DoD.

Results: Small percentage (less than 20%) of stations exhibited statistically significant trends in historical precipitation extremes, while more than 50% of the stations show statistically significant positive trends when future precipitation projections (from two climate models and two emission scenarios) append the past data. Stationary and nonstationary IDF curves with 95% confidence intervals were developed and compared for rainfall durations from one-hour to 10-days and return periods from two years to 500 years for 13 military installations across the United States. The difference in IDF values range from a 25% decrease at Yuma Proving Ground to a 50% increase at Ft. Hood. When future precipitation is considered for the rainfall IDF curves, the storm magnitudes corresponding to longer durations increased for most of the installations with the

increase being higher for the installations located in the central and eastern parts of the country. While the trends for sub-daily storms are mixed, some of the installations (e.g., those located in the south and two in the southwest) showed a negative trend. Consequently, flooding risk may increase in the Midwest and Northwest, but decrease in the southern installations because of future storm trends. The snowmelt effect may change the season of annual maximum precipitation to early spring at Ft. Drum, leading up to a 22% and 25% increase in the 10-year and 100-year storm event magnitudes, respectively. A project website and web-based mapping tool (<https://bogi.evs.anl.gov/dodewa/tool/index.html>) were created to provide access to all the IDF results.

Benefits: The report provides a qualitative assessment and scientific foundation to provide an understanding of flood vulnerability at selected military installations. This work contributes to the DoD's larger goal of improving military readiness for future environmental conditions. Understanding how the intensity and frequency of extreme precipitation events are changing is important for regional risk assessments and adaptation planning. The study provides new understanding of how the frequency and intensity of storm and associated flooding risk may be affected by past and projected changes in extreme precipitation. All methodologies, datasets, and the interactive web-based GIS tool developed during the study will be provided to DoD for use in decision-making and planning exercises.

2. EXECUTIVE SUMMARY

2.1. Introduction

The increase in intensity and frequency of extreme weather events, likely due to a warming climate and an increase in the water holding capacity of the atmosphere, is expected to have adverse effects on critical military installations and operations unless these effects are incorporated into the planning, design, and operations of the military. The majority of military installations worldwide have already faced a rising threat from flooding that can be partly attributed to the increase in storm intensities and frequencies, and the inadequacy of stormwater infrastructures. A recent vulnerability assessment report by the DoD found that, in the United States alone, more than 930 military sites (Figure 1) have been hit by floods in the past 30 years (DoD 2018). A similar report on the effects of a changing climate on military bases across the country found that two thirds of the 79 installations reviewed are vulnerable to flooding (DoD 2019). An estimated \$5 billion is needed to repair and rebuild two air force bases (Tyndall and Offutt) from storms and flood damage that occurred this year, underscoring the need for DoD to better plan and account for the risks posed by flooding and extreme weather. In response to this growing national security issue, Congress recently passed legislation directing the DoD to assess the flood risk and consider future environmental conditions in the design and modification of its military facilities.



Figure 1. Military sites affected by flooding from non-storm surge events over the past 30 years (adopted from DoD 2018)

Adaptation to a rising flood risk starts with quantifying the changes in design storms and their associated impacts on hydrologic processes under a non-stationary and substantially uncertain future climate, and incorporating these changes into future engineering designs and planning. The design storm, often obtained from an intensity-duration-frequency (IDF) curve, needs to reflect the change in extreme rainfall patterns and the various sources of uncertainty involved in constructing the curves. Traditionally, stormwater and flood control infrastructure design relied on the stationarity of the hydroclimatic extremes (e.g., rainfall and streamflow) over the design lifetime of the infrastructure, lasting beyond 100 and 500 years. However, during the last century, more intense and frequent precipitation extremes have been observed in several regions resulting from either a warming climate or long-term climatic variations (Westra et al. 2013). Based on an ensemble of climate model projections and the basic physical relationship between atmospheric water vapor and storms, a warming climate is expected to further increase the intensity and frequency of precipitation extremes in the future (Sillmann et al. 2013). Consequently, the traditional IDF curves can substantially underestimate precipitation extremes and thus, may not be suitable for infrastructure design in a changing climate. For example, much of the drainage system installed over the last several decades used IDF curves that were outdated by as much as half a century, making the system potentially inadequate and vulnerable for flooding under strongly non-stationary precipitation conditions (Mailhot and Duchesne 2010, Rosenberge et al. 2010). It is therefore critical to maintain the IDF curves so they are up-to-date and forward-looking to more accurately reflect the potential changes in rainfall extremes in engineering standards and designs.

The IDF curves, which are commonly constructed using relatively limited records of precipitation extremes, are subjected to bias and uncertainties. The desired storm return periods for a project design usually exceed the record length, making extrapolation of the observed data essential to estimate the storm magnitude corresponding to higher return periods. The frequency analysis methodologies used to construct the IDF curves also contain uncertainties resulted from the choice of homogenous regions, probability distributions, and parameter estimations. In addition, there is a considerable level of uncertainty in climate model predictions of precipitation extremes at the required temporal and spatial resolutions for constructing the IDF curves. Consequently, uncertainty is inherent to the IDF curves and needs to be properly quantified for engineering design and risk assessment applications.

The underlying assumption of using the IDF curves for designing stormwater and flood control structures is that there is a direct relationship between the design storms and design floods. But in reality, other watershed related factors or runoff response dynamics, not only precipitation, are important causes of floods. The assumption may be valid for regions where soil saturation and precipitation extreme are strongly coupled and for regions that are prone to flash floods (e.g., arid and high-slope regions). In these areas, the rainfall amount can be a reasonable indicator of the runoff generated from a given drainage. On the other hand, floods can be caused by non-extreme rainfall falling on saturated soil, as in the Mississippi River Basin, or by the melting of accumulated snow, as in the Rocky Mountains, or by rain on snow, as in the western United States (Berghuijs et al. 2016). Thus, the complexity of floods as a temporal and spatial aggregation of water over a landscape, in comparison to extreme precipitation, necessitates additional considerations other than simply applying the rainfall IDF curves.

2.2. Objectives

The main objective of the project is to revise and update the storm and flood IDF curves for selected military installations by considering the changes in observed and future storm and flood events, effect of snowmelt, and modeling, and data uncertainties. The project involves six interrelated tasks.

The objective for Task 1 is to update the current IDF curves using a regional frequency analysis and the most complete precipitation record available and future projections. The regionalization approach combines data from nearby climatologically similar stations to improve the accuracy of the IDF curves. Incorporation of future precipitation helps to better represent the effects of the changing climate.

The objective for Task 2 is to quantify both the intra-model uncertainty (due to different probability distributions and climate simulations) and inter-model uncertainty (due to parameter estimation) associated with the estimation of the IDF values. Risk evaluation should account for these uncertainties to avoid under design of critical infrastructures dealing with flooding and storm.

The objectives for Task 3 are to perform dynamic downscaling from General Circulation Models (GCMs) to better capture extremes associated with local topographic effects and convective patterns with the Weather Research and Forecasting (WRF) modeling tool, and develop a methodology that can identify and correct the biases in extreme precipitation projections.

The objectives for Task 4 are to effectively update existing IDF curves whenever new precipitation records or projections are available. Instead of reconstructing the IDF curves to incorporate newly available data, a seamless updating approach is required to integrate available precipitation data on a frequent basis. In addition, the project would develop non-stationary IDF curves when the precipitation extreme exhibit significant trends.

The objectives for Task 5 are to develop the runoff IDF curves by considering different site-specific flood-causing mechanisms. The runoff IDF curves allow us to directly characterize the flooding risks and improve the design of stormwater and flood control structures. In addition, this task aims to incorporate snowmelt and accumulation into the IDF curves to better characterize the amount of rainfall that is available for runoff.

The objective for Task 6 is to develop and implement an interactive web-based GIS geodatabase and tool to provide convenient access to the study results for the 13 DoD installations highlighted in the study, particularly the rainfall and runoff IDF curves within their geographic context, under various climate scenarios. The design of the geodatabase and interface provides a framework that can be applied to other military installations or regions of interest. The web-based tool will aid in decision making and planning exercises, especially to assess the vulnerability of existing military installations to extreme rainfall and runoff events, and to adopt design codes for more resilient infrastructure that accounts for climate change.

Moreover, the validity of the current IDF curves was assessed based on the changes in the magnitude and frequency of precipitation extremes under current and future storm conditions. The study provides data and information necessary for assessing the local flood risks at the installation

level and for design guidelines modification to make the installations more resilient to floods taking into consideration the impact of changing climatic conditions.

2.3. Technical Approach

Various statistical and modeling approaches were employed to evaluate, construct and update the IDF curves, quantify the uncertainty ranges, and incorporate future simulations of precipitation extremes and effects of snow accumulation and melt. The Mann Kendell and likelihood ratio test were used to evaluate linear and nonlinear trends in the magnitude and frequency of precipitation extremes. Regional frequency analysis coupled with Bayesian model averaging and parameter estimation methods were used to develop the IDF curves and associated uncertainty intervals. Nonstationary probability distributions with time-varying parameters were used to account for future precipitation and the effect of climate change on the IDF curves. Also, a Bayesian hierarchical method was developed for the frequent update of the IDF curves whenever new precipitation data is available.

A dynamic downscale method using the WRF model was performed to generate high-resolution spatial (12 km) and temporal (30 min) precipitation from climate model projections. The bias in the projections was corrected using a hybridized quantile mapping (HQM) method which was designed to correct extremes in the right tail of the precipitation distribution while preserving the long-term precipitation patterns projected by climate models. The Hydrologic Modeling System (HEC-HMS) hydrological model, with Soil Moisture Accounting (SMA) method for rainfall excess simulation, was used to construct the runoff IDF curves from given rainfall IDF curves. The Utah Energy Balance (UEB) snowmelt model was applied to better understand the runoff behavior associated with snowmelt and rain-on-snow events; these effects were incorporated in the IDF curves. Finally, a project website and web-based GIS mapping tool was developed and populated with the study results for the planned geographic regions and climate scenarios.

2.4. Results and Discussions

The project provides updated IDF curves with 95% confidence intervals for rainfall durations from 1-hour to 10-day and return periods from 2 years to 500 years for 13 military installations across the United States. Unlike the traditional IDF curves, which heavily rely on observed (or historical) precipitation extremes and their stationarity in the future, the updated IDF curves represent the nonstationarity impacts of climate change and effects of snowmelt and accumulation. The curves were used to assess flooding risk under stationary and nonstationary climate conditions.

For all the installations and storm durations (1hr – 10day) we have considered, the historical records of annual maximum precipitation showed no significant spatially consistent trends at either the station or regional levels. Approximately 10%-16% of stations showed statistically significant increasing trends, while only 4%-6% of stations showed decreasing trends in the past. None of the climatologically homogenous regions within our study sites showed significant trends. Relatively more stations in the Midwest (Ft. McCoy and Ft. Riley) and Northeast (Ft. Drum and Aberdeen Proving Ground) showed increasing trends, particularly for storms with daily and longer durations. However, when future precipitations are considered, considerably more stations (> 50%) showed

an increasing trend in storms with daily and longer durations while there was a decreasing trend in storms of sub-daily magnitude at the majority of installations. The differences are not clearly evident in the resulting trends from either the CCSM or GFDL climate models or the RCP 8.5 and 4.5 emission scenarios. Compared to the trend in extreme precipitation of magnitude, relatively more weather stations (50%-90%) showed an increasing trend in the frequency of occurrence of daily extreme precipitation events (heaviest 1% daily precipitation).

Comparing the stationary and nonstationary IDF values, the storm magnitudes corresponding to longer durations increased for most of the installations with the increase being higher for the installations located in the central and eastern parts of the country. For the installations in the south and southwest, the storm magnitudes with sub-daily durations have decreased while they have increased for storms of daily and longer durations.

2.5. Implications for Future Research and Benefits

Adaptation to a rising flood risk entails quantifying the changes in the characteristics of design storms and their associated impacts on hydrologic processes under a substantially uncertain future climate, and incorporating these changes into future engineering designs and planning. The results from our study sites across the United States provide improved and updated IDF curves that can be used to assess the flood risk posed by climate change and its uncertainty on military installations. The updated curves are expected to be used as a scientific basis for understanding the vulnerability of military installations to flooding and contribute to military resilience against the increasing flood trends. Despite the progresses so far, additional research is still needed to identify the level and nature of changes in hydroclimatological extremes, to represent those changes in our design standards and planning, and to provide an accurate assessment of the risks posed by severe storms and floods. There is also a research need to develop a readily available and easy-to-use tool and database to aid in decision making and planning exercises, especially to assess the vulnerability of existing military installations to extreme rainfall and runoff events, and to adopt design codes for more resilient infrastructure that accounts for climate change. The interactive web-based GIS tool from this project has the potential to meet this research need with the inclusion of more military sites into the database and incorporation of advances in the procedures involved for the development of IDF curves and the assessment of flood risk.

3. OBJECTIVE

DoD and the Strategic Environmental Research and Development Program (SERDP) have identified a need to improve the characterization of extreme storms in order to assess the vulnerability of military installations for floods and to adopt design codes for a more resilient stormwater drainage system in view of climate change and uncertainties. The primary objective of this project is to develop and update the rainfall and runoff intensity-duration-frequency (IDF) curves and aid the design of stormwater infrastructure as part of the DoD's broader effort of ensuring installations readiness to climate change and uncertainties. Specifically, the project aims to develop and test new methodologies for creating regionalized, adaptive, probabilistic rainfall and runoff IDF curves by incorporating uncertainties associated with models and data, regional variations of rainfall, and future climate change, and thereby improve understanding of the evolving flooding risk posed by climate change and variability on selected DoD installations. The study involves:

- 1) examining the roles of climate change and uncertainty on IDF curves and related military installations through the use of both historical and projected rainfall data,
- 2) developing a regionalization approach to improve the accuracy of the IDF curves through a better representation of the extreme precipitation spatial variations within a drainage area of interest,
- 3) developing an adaptive methodology for probabilistic estimation of rainfall and runoff IDF curves that can also be dynamically adjusted to incorporate uncertainty and changes in current and future rainfall patterns, as well as newly acquired precipitation data,
- 4) developing dynamic downscale and bias correction approaches, focusing on extreme precipitation, to generate high-resolution spatial and temporal precipitation projections,
- 5) incorporating snowmelt as part of rainfall that potentially contributes to the flood hazard by using a physics-based snowmelt modeling approach to estimate snowpack and snowmelt timing and volume,
- 6) developing an interactive web-based GIS modeling tool to facilitate construction and updating of rainfall and runoff IDF curves, data management, and model testing under different climate and modeling scenarios, and
- 7) demonstrating the applicability of the methodologies and framework for 13 DoD military bases across different climatic and geographic regions.

Also, the project aims to create a fundamental body of knowledge on the effects of climate change and uncertainties on extreme storms for various climate regions and conditions of interest to DoD. Such knowledge is critical for maintaining the IDF curves up-to-date and forward-looking so that the potential changes in rainfall extremes can be reflected in engineering standards and building codes for critical military infrastructures. The final products from the project include: (1) new and updated rainfall and runoff IDF curves with 95% confidence intervals for rainfall durations from 1-hour to 10-day and return periods from 2 years to 500 years for 13 military installations across the United States, (2) rainfall IDF curves with and without the effect of snowmelt and future climate, (3) dynamically downscaled and biased corrected 30-min and 3-km resolutions precipitation and temperature data from CCSM and GFDL models under RCP8.5 and

RCP 4.5 emission scenarios, (4) assessment of risk posed by climate change and variability on existing stormwater drainages at the military installations, (5) an interactive web-based GIS tool containing tabulated and geo-referenced IDF curves data and figures, and (6) user manual prepared in collaboration with the other SERDP projects PIs to assist practitioners adopting nonstationary stormwater designs. The updated rainfall IDF curves and the new runoff IDF curves from this project are expected to provide up-to-date and local design standards and guidelines for storm drainage and flood control structures. The web-based tool will aid in decision making and planning exercises, especially in assessing the vulnerability of existing military installations and adopting design codes for more resilient infrastructure in view of climate change.

4. BACKGROUND

Traditionally, water resources infrastructures are designed to handle a specific storm, also known as design storm, derived from historical rainfall Intensity–Duration–Frequency (IDF) curves that assume rainfall temporal and spatial patterns will remain unchanged in the future. The success of the designs thus depends not only on the accuracy of the IDF characterization of past extreme rainfall events and spatial variation, but also on the future stationarity of the events and proper representation of the different sources of uncertainty involved in developing the curves. However, consensus is growing that rainfall patterns, including frequency, intensity and spatial extent are changing and will continue to do so in the foreseeable future due to climate change, limiting the use of the standard IDF curves for designing reliable stormwater infrastructures under a changing climate. The IDF curves are subjected to various sources of uncertainty resulted from the relatively short-record length and poor-quality storm data, as well as the frequency analysis methodologies used to develop the curves. The use of the curves as a standard design tool for stormwater management systems can also be limited for areas where snowmelt and antecedent soil moisture conditions play important role in generating flood.

4.1. Nonstationarity in Extreme Precipitations and Implications on IDF Curves

Recent analyses of past and future extreme precipitation in several regions of the world have shown the presence of non-stationarity resulting from either climate change or long-term climatic variations (Kunkel et al. 2010, Min et al. 2011, Westra et al. 2013, Zhang et al. 2013, Janssen et al. 2014, Wasko and Sharma, 2015, Fischer and Knutti 2015). In some cases, the extremes have exhibited significant positive trends despite decreases or no trends in mean and total annual precipitations (Groisman et al. 2005, Goswami et al. 2006, Easterling et al. 2017). Extensive data kept by NOAA on weather extremes since 1910 has shown an increasing trend, reaching more than 20%, in one-day extreme precipitation in the contiguous United States (Gleason et al. 2008). Percentage area experiencing precipitation extremes has also increased in the Northern Hemisphere regions over the past half-century (Dittus et al. 2015). Compared to the change in total annual precipitation, the increase in extreme precipitation indicates global consistency over the past century (Donat et al. 2016). The increasing trends in heavy precipitation are expected to continue in the future, with likely intensification in most parts of the world (Groisman et al. 2012, Kharin et al. 2013, Sillmann et al. 2013, Lehmann et al. 2015, Pfahl et al. 2017). Similar to the historical trends, the changes in future extreme precipitations are also expected to be relatively larger than the change in mean precipitation (Berg et al. 2013).

The current and future changes in precipitation extremes can have significant implications on the IDF curves and their applications for engineering designs and flood management, which both traditionally relied on the stationary patterns of extreme precipitation (Madsen et al. 2009, Willems et al. 2012, DeGaetano and Castellano 2017). Much of the drainage system installed in the last several decades use IDF curves that are outdated by as much as half a century, making the system potentially inadequate and vulnerable for flooding under non-stationary precipitation conditions (Nie et al. 2009, Rosenberg et al. 2010, Mailhot and Duchesne 2010, Kessler 2011). Allen and Ingram (2002) reported that climate change might have doubled the risk of the extremely wet weather that causes floods. In the United States alone, the Federal Emergency Management Agency (FEMA 2013) predicted that areas at risk of flooding will increase by 45% by 2100, largely due to the warming of climate. Cheng and AghaKouchak (2014) showed that under a non-stationarity condition, the current IDF curves can substantially underestimate precipitation extremes and thus, they may not be suitable for infrastructure design in a changing climate. Demaria et al. (2017) found that the nonstationarity in extreme precipitation may increase the risk of failure of a hydraulic structure by 25% for a 100-year return period and a project life of 100 years. Sarhadi and Soulis (2017) incorporated the impact of different nonstationarity conditions on the occurrence of extreme precipitation in the Great Lakes area and confirmed the underestimation of extreme precipitation under the stationary assumption. It is thus critical for maintaining the IDF curves up-to-date and forward-looking so that the potential changes in rainfall extremes can be reflected accurately in engineering standards and codes. In order to incorporate effects of climate changes, the next generation IDF need to consider change in extreme events projected by climate models. We performed dynamical downscaling of GCM projections to better capture precipitation extremes associated with the local topographic effects and convective patterns with the Weather Research and Forecasting (WRF) modeling tool, and developed methodology that can identify and correct the biases that are potentially present in both the majority and extreme precipitation events.

4.2. Uncertainty and Spatial Variability of IDF Curves

The uncertainties involved in estimating IDF curves have also received growing research interest, particularly with anticipated climate change and uncertainty about potential impacts of future rainfall intensities and frequencies. The main uncertainties are associated with (1) the frequency analysis of extreme rainfall events as related to the choice of homogenous regions, frequency distribution, and parameter estimation methods (Hailegeorgis et al. 2013); (2) the climate model predictions of extreme rainfall events due to required temporal and spatial resolutions (Frei et al. 2006); and (3) the record size and measurement errors of historical rainfall data, particularly the extreme rainfall (Coles et al. 2003, Huard et al. 2010). For instance, although several probability distributions might reasonably fit the observed or projected series of extreme rainfall data, the estimated quantiles might differ, because estimation of higher extreme quantiles is based on the upper tail of the probability distribution, which is known to be poorly represented in climate models. In addition, use of different parameter estimation methods for selected probability distribution might result in different quantile estimates, as each parameter estimation method has its own strengths and limitations.

On the other hand, because of insufficient information associated with short rainfall series and sparsely distributed rainfall stations, Coles et al. (2003) and Huard et al. (2010) highlighted the importance of assessing uncertainties related to extreme rainfall estimates and propagating those

uncertainties in design decisions and risk assessment. Climate model projections are also subject to numerous uncertainties related to the models and emission scenarios. Frei et al. (2006) compared scenarios from six RCMs to examine for future change of precipitation extremes in Europe and noted considerable differences and uncertainties between model outputs estimating extreme rainfall events. As result of these recognitions, probabilistic IDF curves are getting increasing attention in order to incorporate uncertainty in its estimate of rainfall characteristics and their applications for designing hydraulic structures. Solaiman and Simonovic (2010), for instance, developed a multi-model, multi-scenarios approach to updating IDF curves for potential change and uncertainty in future climate. Huard et al. (2010) introduced a Bayesian approach for estimating the IDF curve from historical rainfall data. Our study extended these earlier efforts and develop an adaptive methodology based on recursive Bayesian estimation to incorporate the different uncertainties readily and reduce uncertainties associated with data size and spatial variations of rainfall through regional frequency analysis, which can allow use of both precipitation data from multiple related weather stations and recently acquired precipitation data in IDF curves.

Another important research trend for improving the accuracy and applicability of IDF curves employs additional precipitation data from neighboring, climatologically similar sites and other relevant data, such as the Tropical Rainfall Measuring Mission (TRMM) radar data (Awadallah et al. 2011), through regional frequency analysis approaches (Hosking and Wallis 1997, Nadarajah 2005, Raiford et al. 2007, Hailegeorgis et al. 2013). Developing IDF curves in general requires the availability of sufficient extreme precipitation data at sites of interest, especially for reliable estimation of rare events such as quantiles with large return periods. However, some regions may have no gauging sites or only a short period with observed records, or precipitation spatial variability might be too large to be represented by precipitation records from a single station. On the basis of regional frequency analysis for an ungauged drainage, Mikkelsen et al. (2005) showed that extreme rainfalls events are often very different spatially, even with minor physiographic differences. In such case, regional or pooled-frequency analysis combining data from climatological similar neighboring sites, based on L-moment (Hosking 1990) approaches for quantile estimations of extreme precipitation events, would be necessary to yield spatially representative IDF curves. Our study developed effective new methodologies for identifying adaptive homogenous regions representing potential variations in rainfall spatial patterns and coverage related to durations and climate change, as well as for updating the curves on the basis of gridded precipitation projections.

4.3. Relationship between Rainfall and Runoff IDF Curves

The importance of linking rainfall and runoff IDF curves was emphasized by Mailhot et al. (2007), Wright et al. (2014), and others, for achieving a more accurate view of potential impacts of storm events on drainage and hydrologic infrastructures. Linking the rainfall IDF curves with runoff IDF curves not only helps assess flood and severe storm impacts on military installations and other relevant structures directly, but it also accounts for human and drainage effects on rainfall-runoff curve generation. In theory, drainage infrastructures should be designed to handle some levels of flood frequency and peak runoff that are not necessarily related directly to rainfall events. However, in practice, the infrastructures are often designed for rainfall characteristics obtained from rainfall IDF curves, under the assumption that extreme rainfall characteristics are a direct representation of extreme runoff or flood characteristics. Depending on antecedent soil

moisture conditions, human interference, and drainage networks and characteristics (e.g., land cover, soil type, slope), there might not be a direct relationship between rainfall and flood frequency. To evaluate the effectiveness of green roofs for flood mitigation, Bengtsson (2005) constructed IDF curves for rainfall and runoff and showed that runoff with a 1.5-year return period corresponds to rain with a 0.4-year return period; the runoff IDF curve for the 0.5-year return period followed the rain IDF curve of a 0.1-year return period. Our study developed methodologies for generating runoff IDF curves from rainfall IDF curves based on the dominate flood generation mechanisms and using suitable rainfall-runoff models and GIS functionalities to characterize drainage areas associated with military installations.

4.4. Effect of Snow Melt and Accumulation on IDF Curves

There have been tremendous studies on precipitation IDF, but no past studies have accounted for the contribution from snow melt and accumulation to the IDF estimates. Snowmelt, especially, the rain on snowmelt events are the most extreme precipitation driven events producing the extreme floods (Jones and Perkins, 2010; Cohen et al. 2015). It is a common feature in various parts of the US, and plays a significant role in generating high streamflows and flooding (Marks et al., 1998; McCabe et al., 2007; Surfleet and Tullos, 2013). One example of worst rain on snow event is the January 1996 flooding across much of the mid-Atlantic and northeast United States. The rapid snowmelt of an unusually deep snowpack and intense rainfall combined to cause catastrophic flooding, which was responsible for as many as 30 deaths and \$1.5 billion in damage (Anderson and Larson 1996). We have developed the IDF curves with direct consideration of intense precipitation over the snowmelt, and quantify the effects of snowmelt.

Finally, the rainfall predictions and associated uncertainties from different climate models and emission scenarios will be compiled and made readily available through our web-based GIS tool to facilitate application of the proposed methodologies in assessing the effects of regionalization, climate change, and uncertainty on rainfall and runoff IDF curves for areas of particular interest to DoD, as well as to make necessary adjustment to the curves.

5. MATERIALS AND METHODS

5.1. Study Sites

Thirteen military installations that are located in different climatology and geographic regions of the United States were used as study sites (Figure 2 and Table 1). The annual precipitations vary from 3.4 inches for Yuma to 65.02 inches for Keesler. Some of the installations have experienced severe flooding in the past. Camp Pendleton was affected by the flash flood in 1993, causing more than \$100 million in damage. Fort Riley was impacted by the “Great Flood” in 1951, leaving some regions under 8 feet of water. Fort Irwin experienced 18 inches of the flash flood in 2013, damaging buildings and roads, and disrupting training and other critical activities for more than weeks. The floods due to Hurricane Katrina in 2005 and Hurricane Gustav in 2008 caused substantial infrastructural damages in Keesler Air Force Base. The Eglin Air Force Base is identified by the SERDP (2013) study as one of the coastal military facilities that will likely experience significant changes to environmental resources and human-made infrastructure due to shoreline retreat, increased flooding, and erosion. We updated the rainfall IDF curves and developed runoff IDF curves for each of these installations, taking into consideration the spatial

variation of precipitation in the associated drainage areas and the impacts of future climate change and uncertainty.

5.2. Data Sources

The project used 15-minute, hourly, and daily precipitation measurements obtained from various sources (Table 1). The daily data for most of the sites were obtained from the National Climatic Data Center's (NCDC) Global Historical Climatology Network (GHCN), Global Summary of the Day (GSOD), and the Natural Resources Conservation Service's SNOTEL database. The hourly data were obtained from the U.S. Hourly Precipitation Data (DSI-3240) and Integrated Surface Global Hourly Data (DSI-3505), while the 15-minute data were obtained from the U.S. 15 Minute Precipitation Data (DSI-3260), which are both archived at the NCDC. Additional local and regional data sources such as AgWeatherNet (for 15-minute precipitations) and 14th Weather Squadron (for hourly precipitation) were used.

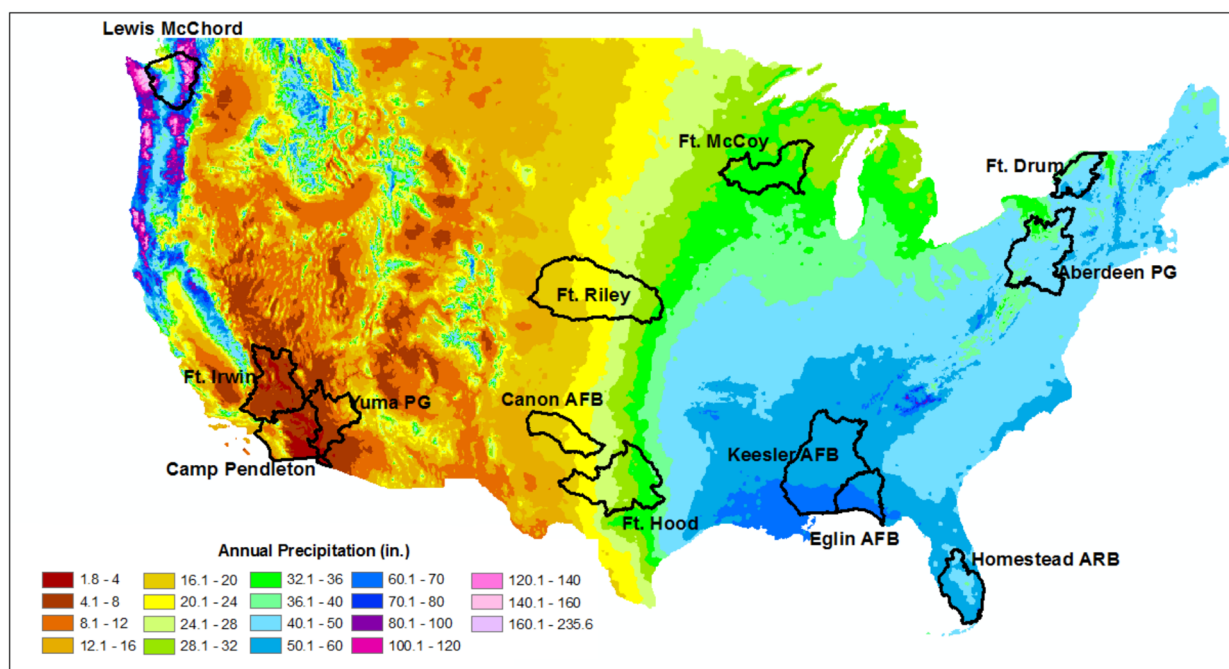


Figure 2. The locations of the HUC-6 watersheds associated with the 13 military installations. The background color map is the 30-year average annual precipitation obtained from the PRISM Climate Group, Oregon State U.

Table 1. Basic characteristics of the 13 military installations and the precipitation datasets used for the project. The watersheds located close to each other are combined for the regional frequency analysis.

Installation	Drainage area (10 ⁶ ha)	Annual Rain (Snow), in	Elevation AMSL (ft)	Disruptive Floods	Daily Stations (GHCN & GSOD)	Hourly Stations (DSI- 3240 & DSI- 3505)	15-min Stations (DSI-3260)
Lewis McChord	3.01	49.8 (7.6)	322		557	130	115
Camp Pendleton	5.86	11.1	78	1993, 2010	727	247	227
Fort Irwin	6.20	15.2 (8.2)	2,454	2013, 2010			
Yuma PG	4.44	3.4	4,144				
Fort Riley	11.64	35.7 (17.6)	1,063	1951, 1993	872	303	297
Fort Hood	9.14	36.8 (0.6)	1,015	2016	1051	377	289
Cannon AFB	3.78	18.5 (11.1)	4,295				
Keesler AFB	13.05	65.02	33	2005, 2008	788	314	276
Eglin AFB	3.84	65.3	87				
Fort Drum	2.21	36.0 (78.5)	144		1517	254	244
Aberdeen PG	6.53	41.8 (20.2)	57				
Fort McCoy	4.32	32.3 (44.4)	838		408	150	138
Homestead ARB	5.21	62.4	7	2012	132	254	51

In order to further evaluate the trend and non-stationarity in extreme precipitation using a relatively long record data (about 100 years), few representative stations around the 13 military installations were selected to aggregate the precipitation data when there is no single station with a long record close to the military installations. Figures 3 and 4, respectively, show the locations of the stations and the aggregated AMS. These data were also used to study the possible correlation between annual maximum precipitation and the large-scale climatological variabilities, such as the Pacific decadal oscillation (PDO) and the North Atlantic Oscillation (NAO)

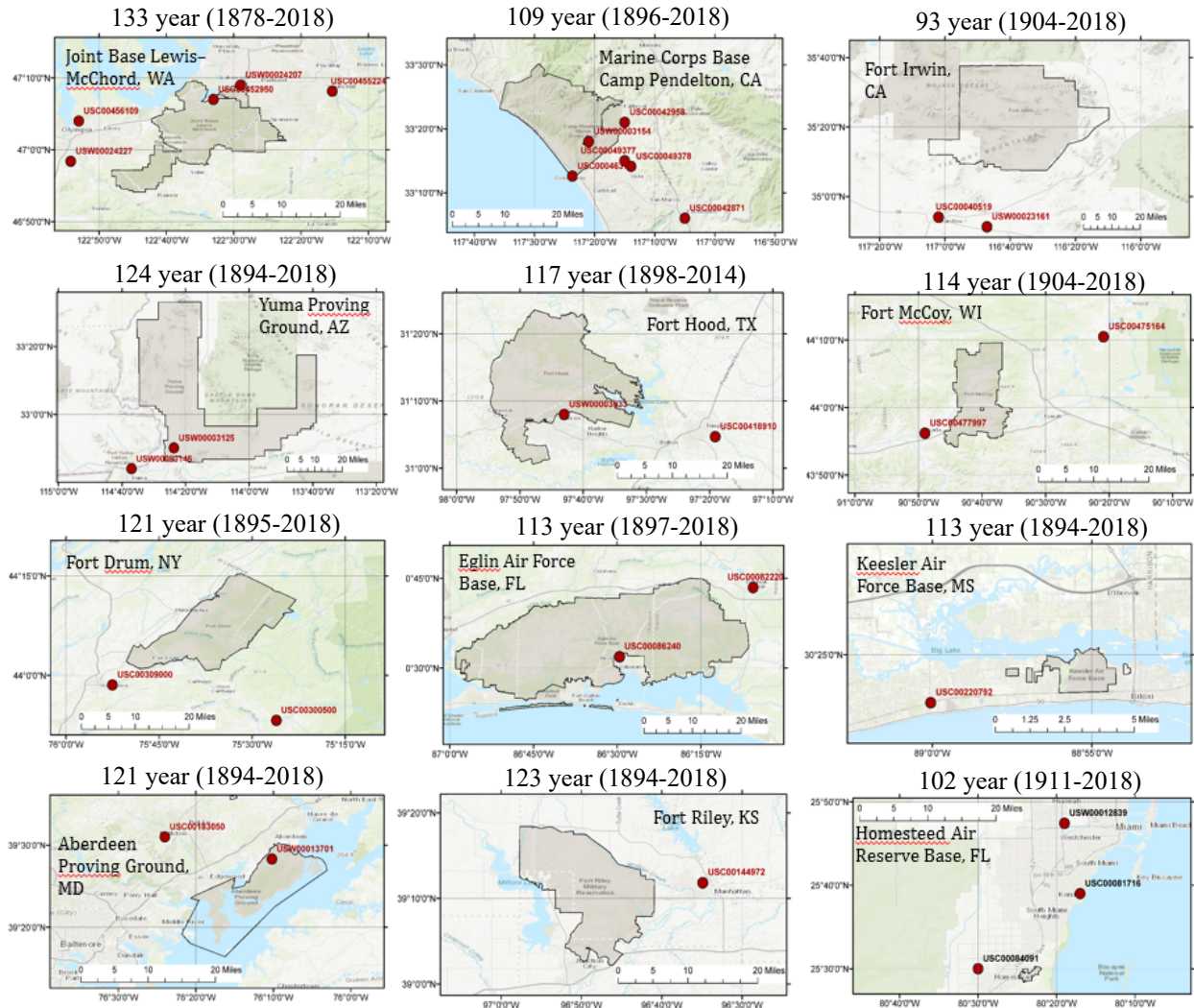
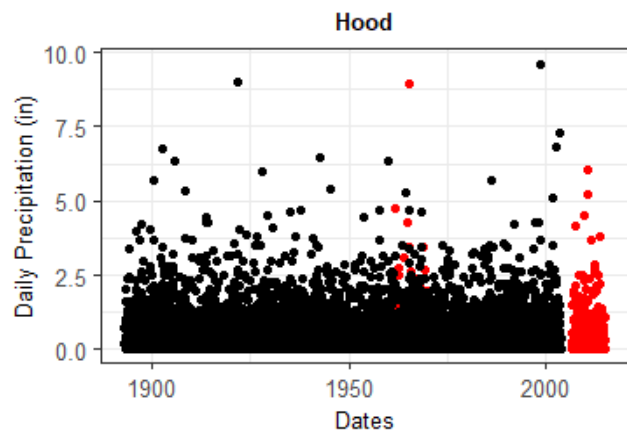
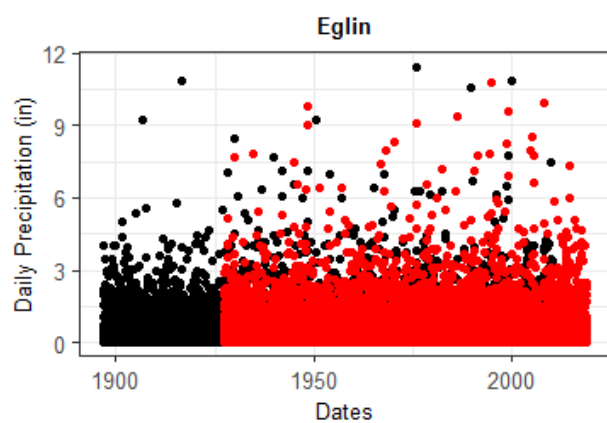


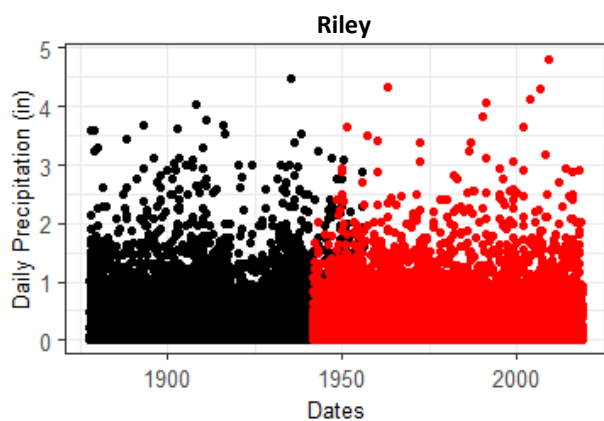
Figure 3. Locations of the weather stations and record ranges used to develop the long-term precipitation data for the trend analysis of extreme storms. The highlighted regions are the military installations.



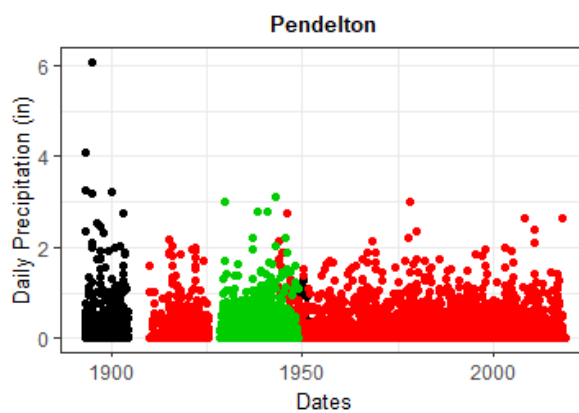
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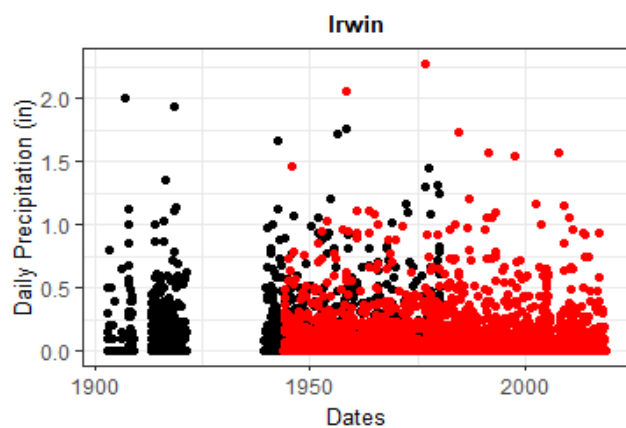
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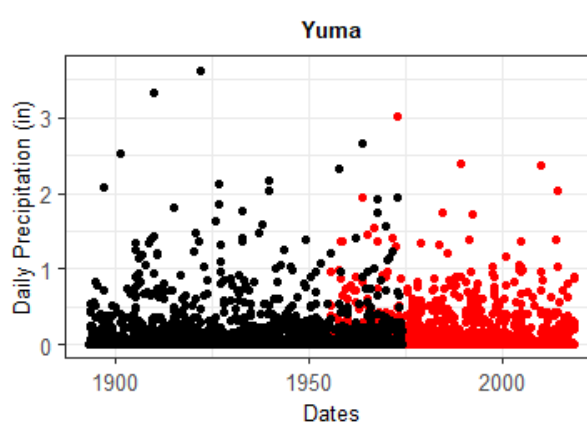
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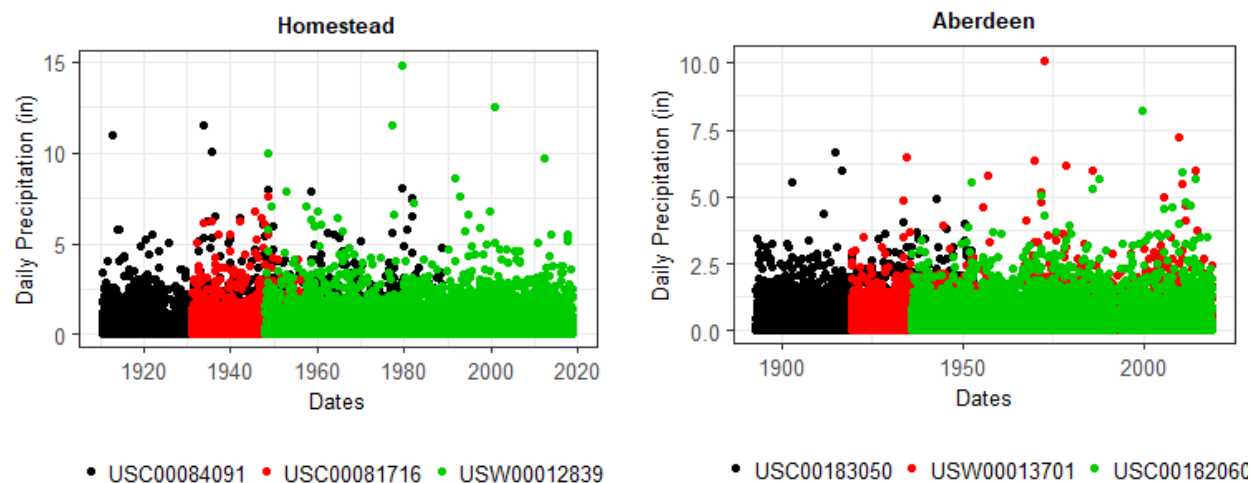


Figure 4. Long-term daily precipitation data that were developed by combining data from neighboring stations. The recent records were used when there were data overlaps

5.3. Data Screening for Measurement Errors

Stations with minimum 20 years and 15 years record lengths were selected for the daily and hourly datasets. The record for a particular year was removed when the record coverage for the same year was less than 90% for daily or less than 70% for hourly and 15-minute data. In order to screen the data for potential measurement errors and outliers, we have conducted the discordancy test based on Hosking and Wallis (1997) for all the AMS series at each installation. The L-moments and their ratios were estimated for the AMS after normalizing them by the average annual precipitations. The L-moment ratios from each precipitation station are then compared to the regionally average L-moment ratios to determine the discordancy measure (D) and identify statistically unrelated stations within the study area. Hosking and Wallis (1997) suggested a critical value of D to be 3 for a station within a region contains more than 15 member stations. Figure 5 shows the discordant stations for the 1-day AMS in Lewis-McChord, Fort Irwin, Camp Pendleton and Yuma PG. The AMS data from those stations with higher discordancy measures were further examined to determine the sources of the discordancy. If the likely reason for a higher D value was measurement errors, the associated annual maximum precipitation would be replaced by the next maximum value during the same year. Figure 6 shows the 1-day AMS for three discordant stations ($D > 3$), indicating some of the discordances were resulted from possible measurement errors and removed from the daily data.

In addition to assisting in identifying abnormalities in the AMS, the discordancy measure can aid in identifying homogeneous regions. If a station is discordant in a particular region, it could be moved to another region, which may have relatively similar L-moment ratios. This is discussed further later in the section related to the identification of homogeneous regions.

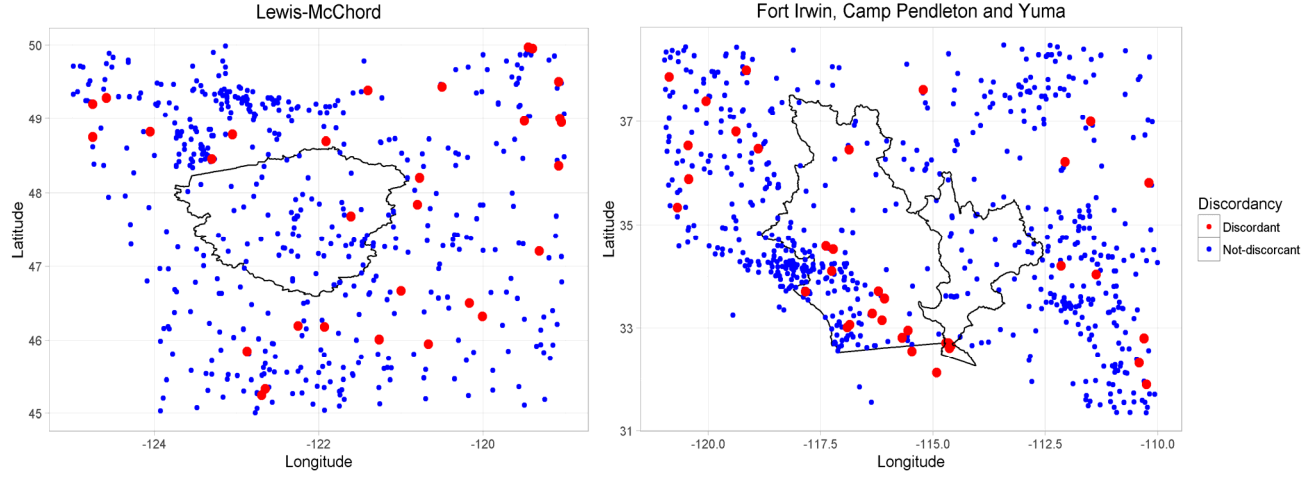


Figure 5. Stations with daily precipitation records showing discordant stations ($D \geq 3$) in the large red dots.

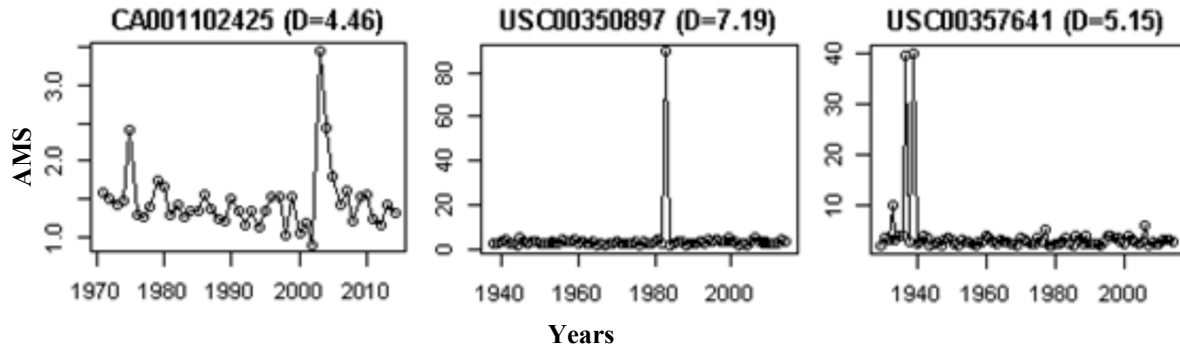


Figure 6. The AMS (inches) for stations which are considered to be discordant ($D > 3$), indicating the presence of potential measurement errors.

5.4. Data Analysis for Trends, Correlation and Change in Variance

In addition to identifying the potential measurement errors, the AMS for each station and duration was evaluated for the presence of trend, correlation, and change in inter-annual variance. Like most statistical analyses, frequency analysis requires the data to be stationary and independent. The Mann–Kendall statistics (Z) (Mann 1945, Kendall 1975), which uses the Z -test and less affected by outliers in data, was applied to evaluate the stationarity and presence of a linear trend in the AMS. When $|Z| > Z_{crit}$, the null hypothesis of no trend can be rejected, and the data is considered to have a significant trend. Z_{crit} is 1.96 for the 95% confidence level or 5% significance level. The Breusch–Godfrey test (Breusch 1978, Godfrey 1978) was used to detect serial correlations up to third order in the AMS. The test is more general than the commonly used methods, like the Durbin–Watson statistic, which is only valid for testing the possibility of a first-order autocorrelation. The Levene test (Levene, 1960) was used to test for homogeneity of variance

in the AMS at the 5% significance level. The test has been proven to be less sensitive to non-normality in data than some other commonly used tests. The test evaluates whether two sub-samples in a given population have equal or different variances. In our case, we have divided the AMS to four sub-samples and evaluated the change in variances. Both tests were performed for precipitation data from individual weather stations and from combined stations within climatologically similar regions. Since the project used a regional frequency analysis, the results from the regional tests were used to decide a stationary or non-stationary or transform the data for developing the IDF curves.

5.5. Identification of Homogeneous Regions

Rainfall frequency analysis to develop an IDF curves uses precipitation measurements obtained from either a single weather station (also called at-site frequency analysis) or a group of weather stations which have statistically similar characteristics of extreme rainfalls (also called regional frequency analysis). In this project, regional frequency analysis (RFA) was used to develop the rainfall IDF curves. The approach combines the data from a cluster of similar sites often called homogeneous region or pooling group to improve the reliability of the precipitation quantiles estimates at any site in the group (Wallis et al, 2007). The homogeneous regions for each storm duration were identified using, first, the location information of the weather stations (latitude, longitude and elevation) and mean annual precipitation. The initial regions were then evaluated and adjusted to determine the homogeneous regions based on the discordancy test of the AMS from the stations within the initial regions. Figure 7 summarizes these procedures.

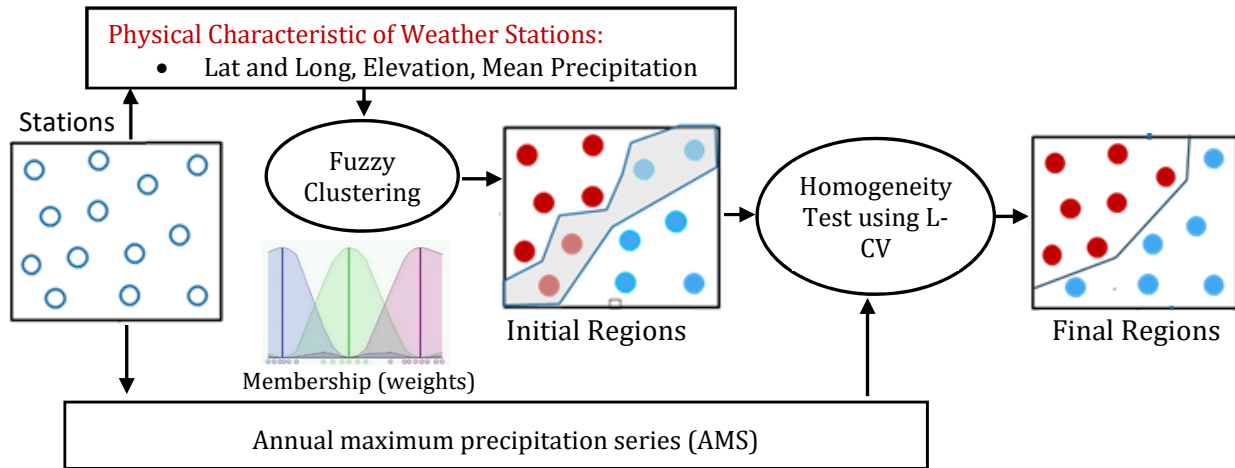


Figure 7. The procedure to identify climatologically homogeneous regions.

The Fuzzy C-Means (FCM) clustering approach (Dunn 1974) was used to identify the initial regions. The FCM algorithm is similar to the K-means algorithm except that instead of assigning each site to only one cluster, the degree of membership is provided to each site based on the likelihood of the site to belong to different clusters. For example, a site near the edge of a

cluster may belong to the given cluster to a lesser degree than sites close to the center of the cluster (Figure 7). The FCM algorithm involves (1) forming an initial set of k groups randomly, (2) estimating the centroid of each group and the membership values for each station, (3) creating a new cluster by connecting each site with the closest centroid, (4) recalculating the centroids for the new clusters, and (5) repeating step 3 and 4 until convergence or a minimum total intra-cluster variance (distance or squared error objective function) given in equation 1 below is achieved (Ayvaza et al. 2007).

$$D_v = \sum_{i=1}^N \sum_{k=1}^K m_{ij} |x_i - c_k|^2 \quad (1)$$

where x_i is the standardized vector of the i th station's attributes (lat/long, elevation and mean precipitation), c_k is the centroid of cluster k , K is the total number of cluster, N is total number of stations, m_{ij} is the degree of membership of x_i to be in cluster k and computed using:

$$m_{ij} = \frac{1}{\sum_{j=1}^K \left(\frac{|x_i - c_k|}{|x_i - c_j|} \right)} \quad (2)$$

During the iteration, the membership m_{ij} and the cluster centers c_k will be adjusted. After convergence, each station is assigned to the cluster for which it has the highest degree of membership.

The initial regions obtained from the clustering analysis may not necessarily contain weather stations with similar statistical characteristics of the extreme precipitations. In order to have similar or homogeneous regions, the initial regions were adjusted based on the homogeneity test developed by Hosking and Wallis (1997). The test compares the observed dispersion of the L-moments among stations within a region with the theoretical dispersion limit for a homogeneous region with an equal number of stations and record lengths as the observed data. The following equation was used to compute the dispersion in L-moments from the observed data:

$$V = \frac{\sum_{i=1}^N n_i (t^i - t^R)^2}{\sum_{i=1}^N n_i} \quad (3)$$

where t^R and t^i are the regional average L-moment ratio and the L-moment ratio for station i , respectively, n_i is the sample size at station i , and N is the number of stations in a region. The theoretical L-moment ratios were computed by randomly generating datasets with an equal number of stations and record lengths as the observed data from the Kappa distribution, which was fitted to the regional average L-moment ratios. 1,000 datasets or realizations were generated using the Monte Carlo approach. The mean (μ_V) and the standard deviation (σ_V) of the dispersions are computed from the realizations and used to determine the homogeneity test statistics (H) as follow:

$$H = \frac{V - \mu_v}{\sigma_v} \quad (4)$$

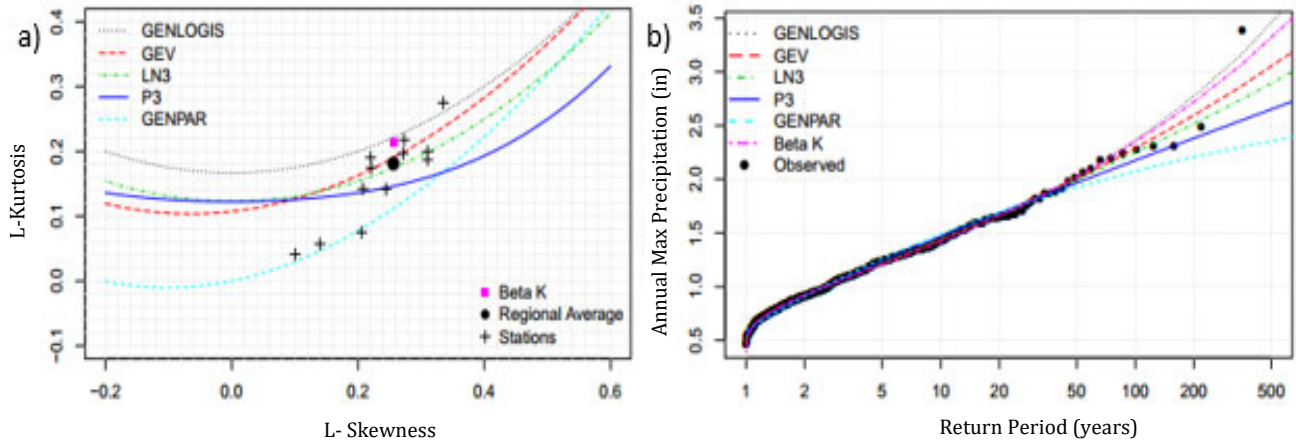
According to Hosking and Wallis (1997), a region is considered to be “acceptably homogeneous” if $H < 1$ and “definitely heterogeneous” if $H \geq 2$. In this project, the critical value of H was considered to be 2 due to the additional variability in the precipitation measurement. If an initial region failed to be homogeneous (i.e., $H > 2$), the region will be revised by removing stations with higher discordance (D) values and replacing them with other stations until the region become homogeneous. The membership information from the FCM clustering was used to assist moving stations from one region to the other during the adjustment of the initial regions to the homogeneous regions.

5.6. Regional Probability Distributions

Once the homogeneous regions were identified and validated, the proper probability distribution models for each region were determined using the L-moment ratio diagram (Figure 8a) and the following Z-statistics (Z^{Dist}) for the goodness-of-fit measures (Hosking and Wallis 1997):

$$Z^{Dist} = \frac{t_4^R - \tau_4^{Dist} + \mu_4}{\sigma_4} \quad (5)$$

where, t_4^R is regional average L-kurtosis (L-Ck), τ_4^{Dist} is theoretical L-Ck for the fitted probability distribution. The realizations from the Kappa distribution, which were used for the homogeneity test, were used again to determine the mean (μ_4) and standard deviation (σ_4) of the difference between t_4^R and L-Ck for each realization. Five commonly used probability distributions namely Generalized extreme value (GEV), Generalized Pareto (GP), Generalized logistic (GLO), Generalized normal (GNO) and Pearson type-3 (PE3) were used to fit the combined AMS for a given region. The distribution was considered acceptable at 90% confidence level when the $|Z^{Dist}| \leq 1.64$. When none of the above distributions met this criterion, the four parameter Kappa distribution was used.



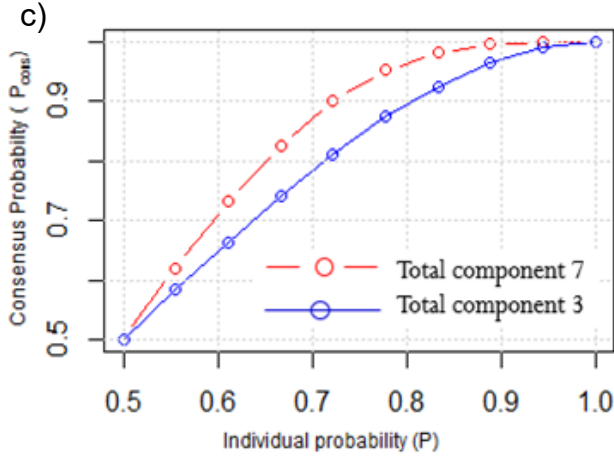


Figure 8. a) the L-moment ratio diagram to select the probability distributions (lines) based on the closeness of the lines to the regional average L-Skewness and L-Kurtosis (black dot), b) the probability distributions fitting to the observed IDF data, c) the probabilities of success for a single (x-axis) and combined (y-axis) binomial distributions using 4 above-average performing (probability of success is greater than 0.5) distributions out of 7 total distributions and 2 distributions out of 3 total distributions. For example, combining two

binominal distributions with each having 0.7 probability of success will improve their combined probability of success to 0.8.

5.7. Bayesian Model Averaging

Instead of selecting a single best-fitted probability distribution, in this project, we selected all the distributions that satisfy the Z-statistics goodness-of-fit criterion. The precipitation quantile estimates from these distributions were combined using the Bayesian Model Averaging approach (BMA) (Hoeting et al., 1999; Raftery et al., 2005). As demonstrated in the Figure 8c, besides its intuitive convenience, there is a theoretical justification for averaging competent models (in our case probability distributions) to provide improved estimates of the precipitation quantiles or the IDF curves. The figure shows that the combined models perform better than any of the individual component models as long as we use independent and above average performing models (Dietterich, 2000). In addition, even though the individual model performances are nearly equivalent for the fitting datasets (Figure 8a), the selection of a single model can result in significant errors when they are applied to extrapolate the extreme precipitations for a longer return period (Figure 8b).

The BMA combines model predictions using weights computed based on their posterior performances. The mathematical formulation of BMA is:

$$P(Q|T, D) = \sum_{i=1}^m P(Q|M_i, T, D) P(M_i|D) \quad (6)$$

where $P(Q|T, D)$ is the predictive probability of the extreme precipitation intensity Q for a given duration and return period (T) based on the consensus of m models, D is the observed AMS data, $P(Q|M_i, T, D)$ is the prediction by model M_i while $P(M_i|D)$ is the posterior model performance used to weight the model prediction. The BMA is implemented using Bayes factor (Hoeting et al., 1999), which allows the direct use of the Z-statistics values as priors to the averaging. The

procedure is detailed in Liang et al. (2011) and briefly outlined as follows. Under the Bayes factor approach, the model posterior $P(M_i|D)$ is estimated using the following formulation:

$$P(M_i|D) = \left[\sum_{j=1}^m \frac{P(M_j)}{P(M_i)} B_{ji} \right]^{-1} \quad (7)$$

where $P(M_i)$ and $P(M_j)$ are priors for models M_i and M_j , respectively, B_{ji} is the Bayes factor that measures the relative likelihood of the two models and computed using:

$$B_{ji} = \frac{P(D|M_j)}{P(D|M_i)} \quad (8)$$

The priors of the models $P(M)$ were estimated based on the Z-statistics values, while the likelihoods $P(D|M)$ were estimated based on fitting errors of the models to the IDF dataset. In comparison to other multi-model averaging techniques, BMA has several favorable features, including the relative ease of its computational implementation, its ability to incorporate additional information as a prior and providing interpretable weights. The BMA in this project was built on the results of L-moment based RFA by using all models (probability distributions) that are ranked by the Z-statistics. In this regard, the approach preserves the benefits of the L-moment approach. Several model performance measures were employed to evaluate the BMA and the individual models. These include the Taylor diagram (Taylor 2001), which is composed of the correlation coefficient, standard deviation, and centered root mean square errors; the modified Anderson-Darling metric (Ahmad et al. 1988); and the bootstrap analysis.

5.8. Bayesian Parameter Estimations

The Bayesian approach was used to estimate the posterior distribution of the parameters $p(\theta|D, M_i)$ for a given probability distribution model M_i and AMS data D using:

$$P(\theta|D, M_i) = \frac{P(D|\theta, M_i)P(\theta|M_i)}{\int_{\theta} P(D|\theta, M_i)P(\theta|M_i)d\theta} \quad (9)$$

where: $P(\theta|M_i)$ is the prior distribution of the parameters, $P(D|\theta, M_i)$ is the likelihood distribution which measures the likelihood that the observed AMS data (D) come from the given distribution model M_i with parameters θ . Since the integral in the above equation is difficult to solve analytically, Markov Chain Monte Carlo (MCMC) simulation using Metropolis-Hasting algorithm was used to generate a set of parameters that were used to compute the likelihood and the normalized factor (the denominator in Eq. 9). For an efficient implementation of the Metropolis-Hasting algorithm, a multivariate normal distribution was used as a proposal distribution (Reis and Stedinger, 2005). The variances of the proposal distribution were tuned using a trial-error method to get reasonable acceptance rate, which represents a percentage of times a new sampled data is accepted. A high acceptance rate indicates poor mixing of the chain while a low acceptance

rate means rejecting too many candidate samples resulting in an inefficient algorithm. Based on recommendations by Roberts et al. (1994) and Gamerman (1997), the acceptance rate in this project was kept approximately 0.3. After computing the posterior distribution of the model parameters, the posterior distribution of extreme precipitation quantiles $P(Q|M_i, T, D)$ for a given model M_i , return period T and AMS data D was computed by marginalizing the model prediction $p(Q|\theta, D, T, M_i)$ over the posterior distributions of the parameters as follow:

$$P(Q|M_i, T, D) = \int_{\theta} P(Q|\theta, D, T, M_i)P(\theta|D, M_i)d\theta \quad (10)$$

The above integral was solved using the MCMC approach by sampling from the posterior distributions of the parameters $P(\theta|D, M_i)$ and using those parameters in the model M_i to predict the extreme precipitation quantiles $P(Q|\theta, D, T, M_i)$.

5.9. Dynamic Downscaling of Future Extreme Precipitation

Several previous studies have indicated that the general circulation models (GCMs) at spatial resolution of 50 km or greater cannot resolve convective patterns that lead to extreme events, such as extreme precipitation (Solomon et al., 2007; Kundzewicz, et al., 2007; Christensen and Christensen, 2003; Fowler, et al., 2007; IPCC, 2007). The statistical downscaling also has a limited ability to delineate storm events governed by local weather conditions, such as the convective thunderstorm, without physical process resolved at a fine resolution. In order to capture future extreme storms, we used dynamically downscaled projections that provide the only reasonable method for representing small-scale physical processes and is able to include orographic effects, land-sea contrast, and land surface characteristics (Christensen and Christensen, 2007). This approach is better suited to extreme value analysis at the catchment scale, making them particularly useful for local climate impact studies for extreme storm events (Teutschbein and Seibert, 2012).

A regional-scale dynamically downscaled model was developed at a spatial resolution of 12 km covering CONUS by using the Weather Research and Forecasting (WRF) modeling tool. The WRF model considers the regional/local topography, land surface processes, detailed cloud physics, and radiative transfer schemes (Giorgi et al., 2012). These attributes facilitate modeling of the localized advection processes that govern the magnitude of extreme precipitation events. The WRF output may result in increased inter-annual variability (Mo et al. 2005) and precipitation intensity (Roads et al., 2003) compared to the results from GCMs. The three sets of output data from GCMs available from CMIP5 include NCAR's Community Climate System Model version 4 (CCSM4) emission RCPs 4.5 and 8.5 (Gent et al., 2011).and NOAA's Geophysical Fluid Dynamics Laboratory Earth System Model (GFDL-ESM2G) emission RCP 8.5 (Taylor et al. 2012).

The domain of WRF regional climate model (WRF-RCM) for dynamic downscaling has approximately 4.28 million grid cells ($450 \times 340 \times 28$) with high spatial resolution of 12 km and temporal resolution of 30 minutes (Kotamarthi et al. 2016). Total simulations of 180 years, including 30 historical years (1975-2004) and 30 future years (2035–2064), were conducted to downscale CCSM4 and GFDL-ESM2G output under RCPs 4.5 and 8.5. The simulations were

performed on the National Energy Research Scientific Computing Center (NERSC) cluster (Cori and Edison). The dynamic downscaling has relatively high computation time and took about 800,000 core hours.

The precipitation and temperature output are saved every 30 min. Six near-surface variables, including water vapor mixing ratio, surface pressure, zonal and meridional wind, short/long wave heat flux, are saved every hour, other large-scale variables, and vertical profiles are saved every 6 hours. The historical data in 1975-2004 were used for extensive bias correction as discussed in the following section.

5.10. Bias Correction of the Downscaled Extreme Precipitations

In order to incorporate the dynamically downloaded climate projections into the development of IDF curves, the future projections from the WRF model need to be evaluated for any potential biases prior to the IDF development. The main objective is to identify and correct the biases that are potentially present in both the majority and extreme precipitation events. Two steps are considered. First, we aimed to develop a bias correction methodology that is effective for correcting biases in both the extremes and the majority of future precipitations, and that could capture the changes seen in the WRF model projections between the historical and future periods. Second, we developed a method for incorporating the effects of the changing climate on extreme precipitation into the extreme distribution and IDF curves.

Despite the high resolution (12-km) of the dynamically downscaled data from the WRF model, the degree of bias in the precipitation output is still significant enough that its direct use in climate impact studies is precluded (Ehret et al., 2012). To account for and correct the unrealistic magnitude of precipitation seen in the model projections, we use a post-processing step of bias correction. The bias corrected projection data is then used to develop IDF curves and therefore may have a large impact on the final results of the project, making it a crucial step in the data preparation process for this project.

Many bias correction methods exist, but most fall into one of a few categories: linear scaling, local intensity scaling, delta-change, and quantile mapping (Thiemeßl, et al., 2011; Watanabe, et al., 2012; Lafon et al., 2013; Teutschbein and Seibert, 2012). Review papers in recent years have identified quantile mapping, which corrects for errors in the shape of the distribution, as superior to other methods because of its ability to correct biases in the higher moments of the climate variable distribution (Teutschbein and Seibert, 2012; Chen, 2015; Gudmundsson, et al., 2012; Watanabe, et al., 2012; Thiemeßl, et al., 2011). However, only a small subset of these studies has demonstrated success in correcting the right tail of the precipitation distribution, while almost all assume stationarity between the past and future climate.

In this project, we evaluated the existing most promising quantile mapping methods, such as the quantile delta mapping (QDM) (Cannon et al. 2015), modified quantile mapping (MQM) (Li et al. 2010; Wang and Chen 2014), and equidistant quantile mapping (EQM) (Srivastav et al. 2014) and identified a further improvement by introducing new method, hybridized quantile mapping (HQM). The detailed comparisons and improvements are documented in a separate manuscript submitted for publication (Jared et al., 2019). The HQM technique is designed to correct extremes in the right tail of the precipitation distribution while considering non-stationarity of the climate

conditions and preserving the long-term climate change signals in the extremes projected by RCM output so that the data can be reliably used in an IDF study. The proposed method corrects the quantiles with a modified MQM method (Wang and Chen, 2014) and the extremes separately with EQM method using extreme value theory. The study also aims to develop next generation IDF curves with non-stationary extreme value analysis using HQM-corrected climate change projections.

A long-term gridded observation dataset of 4km resolution and daily time step was obtained from PRISM Climate Group (Di Luzio, 2008) for the historical period (1981-2004) and spatially interpolated to the WRF RCM grid spacing. These data are generated using climatologically-aided interpolation, which allows the long-term average climate to inform the spatial pattern of climatic conditions for a given day.

A general process of bias correction with HQM is illustrated in Figure 9, in which extreme values were corrected separately from the values in lower percentiles. The upper 1% of values (i.e. points over threshold, or POT) were isolated from the observed, historical model, and future model precipitation. The lower 99% of values (i.e. points under threshold, or PUT) were further split into four subsets by seasons for each of observed, historical model, and future model datasets, and each subset corrected according to the equation

$$PUT_c = put_{fut} * \frac{F_{emp,obs}^{-1}(F_{emp,fut}(PUT_{fut}))}{F_{emp,hist}^{-1}(F_{emp,fut}(PUT_{fut}))} \quad (11)$$

where put_{fut} are the model future PUT for a given seasonal subset, $F_{emp,fut}$ is the empirical CDF function for the model future PUT, and $F_{emp,obs}^{-1}$ and $F_{emp,hist}^{-1}$ are the inverse empirical CDF functions for the observed and model historical PUT, respectively. The PUT_c is the corrected PUT precipitation for a given season.

Similarly, the POT are corrected according to the equation

$$POT_c = POT_{fut} * \frac{F_{GP,obs}^{-1}(F_{GP,fut}(POT_{fut}))}{F_{GP,hist}^{-1}(F_{GP,fut}(POT_{fut}))} \quad (12)$$

where POT_{fut} is the model future POT, $F_{GP,fut}$ is the Generalized Pareto (GP) CDF function for the model future POT, and $F_{GP,obs}^{-1}$ and $F_{GP,hist}^{-1}$ are the inverse GP CDF functions for the observed and model historical POT, respectively. The POT_c is the corrected POT precipitation.

In addition, the number of rain days is also adjusted for each of the PUT seasonal subsets according to the equation

$$nr_c = nr_{fut} * \frac{nr_{obs}/t_{obs}}{nr_{hist}/t_{hist}} \quad (13)$$

where nr_c is the number of rain days we expect in the corrected precipitation distribution, nr_{fut} , nr_{obs} , and nr_{hist} are the number of rain days in the modeled future, observed, and modeled historical time series respectively, and t_{obs} and t_{hist} are the total number of days in the observed and modeled historical time series respectively. We expect $nr_c < nr_{fut}$ in all cases since RCM data tends to overestimate the number of rain days.

The PUT_c seasonal subsets are linearly interpolated to the length of each season's nr_c value. As noted above, $nr_c < nr_{fut}$ for all seasons, so each interpolated PUT_c is then augmented to the length of nr_{fut} by adding the appropriate number of zero precipitation days. Each resulting time series is finally reordered according to the dates of the season's original PUT_{fut} . Therefore, the largest value of each season's PUT_c assumes the same date as the largest value of the same season's PUT_{fut} , the second largest value of each season's PUT_c assumes the same date as the second largest value of the same season's PUT_{fut} , and so on. Each value of the POT_c assumes the same date as it's corresponding POT_{fut} value, resulting in an ordered and bias corrected future modeled precipitation time series.

Potential outliers in the corrected data are identified by isolating the largest precipitation value in each year and calculating an upper threshold limit equal to $\text{mean} + 2.563 * \text{sd}$ of the annual maximums. Any values above that limit are removed from the data. Daily corrected data is temporally downscaled to hourly by distributing each 24-hour total according to the same proportions as seen in each 24-hour period of the model future data. For example, it rained 1 inch in the first hour of December 1st, 2035, and $\frac{1}{2}$ inch in the second hour for a total of $1 \frac{1}{2}$ inches in that day. If the corrected 24-hour total on that day is $\frac{3}{4}$ inch, the corrected first hour becomes $\frac{3}{4} * \frac{1}{1 \frac{1}{2}} = \frac{1}{2}$ inch and the corrected second hour becomes $\frac{3}{4} * \frac{\frac{1}{2}}{1 \frac{1}{2}} = \frac{1}{4}$ inch.

Finally, corrected hourly data is interpolated to station locations using a simple IDW algorithm. The interpolated corrected hourly data at each station are representative of realistic precipitation values at the station level because using a high-resolution observational data set (4km) serves to further spatially downscale the area-averaged RCM output to the local-level resolution of a climate station. We found that correcting the 12km RCM with 4km PRISM data produces precipitation magnitudes very close to that seen in the original station data (Figure 10).

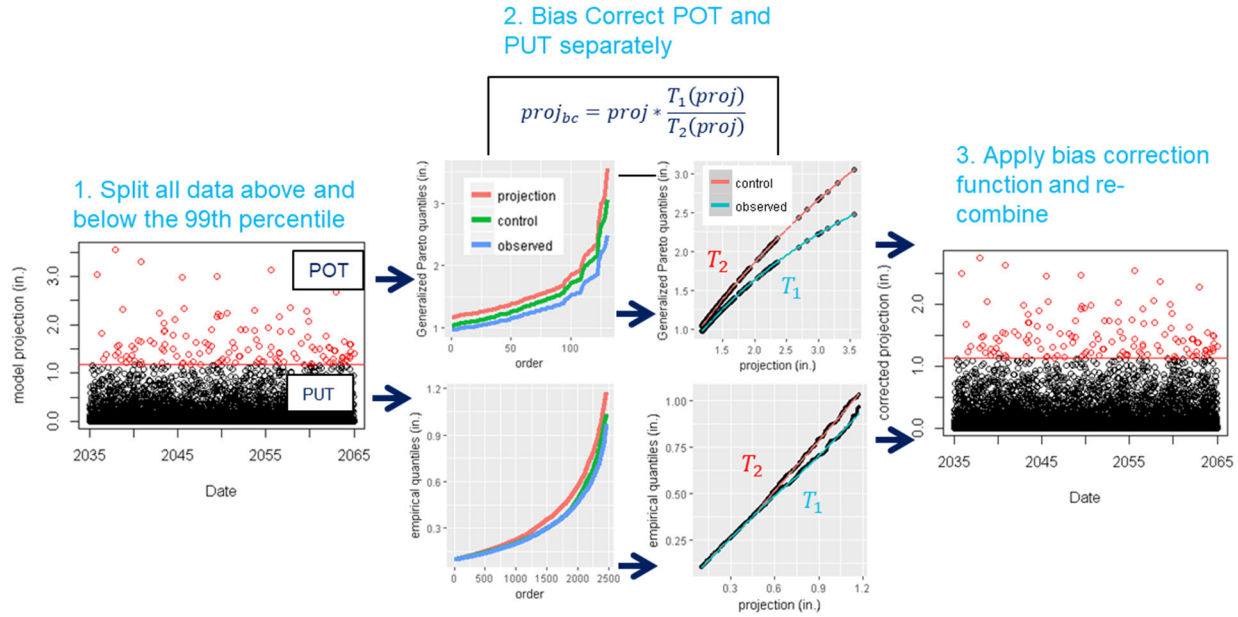


Figure 9. Process of HQM bias correction, in which extreme values were corrected separately from the values in lower percentiles.

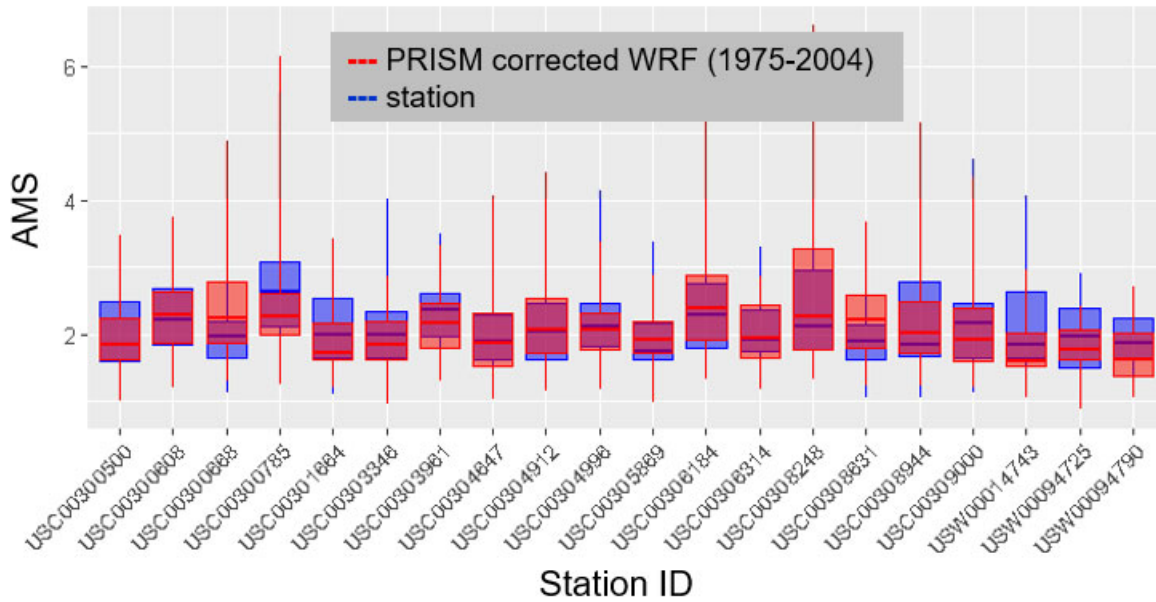


Figure 10. Comparison of annual maximum series (inches) from the WRF-RCM precipitations corrected by HQM method with PRISM data and observed precipitation at sample stations.

5.11. Updating the IDF Curves for the Future and Recently Observed Rainfall Data

We incorporated the potential change in extreme precipitation over time using either the recursive Bayesian approach in the absence of significant trends or adopt non-stationary extreme value distributions in which the location parameter is allowed to vary with time.

5.11.1. Bayesian Update of the IDF Curves

The Bayesian parameter estimation method described above has the flexibility to update the estimated posterior distributions of the parameters for a given model when new rainfall data are available. In this case, the posterior parameter distribution obtained from historical rainfall data ($P(\theta|D_{Hist}, M_i)$ in Eq. 9) will be used as prior, while the new rainfall data together with the historical data ($E = \{D_{New}, D_{Hist}\}$) will be used for the likelihood $P(E|\theta, M_i)$ calculation and to recursively update the parameters posterior distributions and the associated the IDF curves as shown in equation below (Figure 11). The procedure will be repeated whenever new rainfall data are available.

$$P(\theta|E, M_i) = \frac{P(E|\theta, M_i)P(\theta|D_{Hist}, M_i)}{\int_{\theta} P(E|\theta, M_i)P(\theta|M_i)d\theta} \quad (14)$$

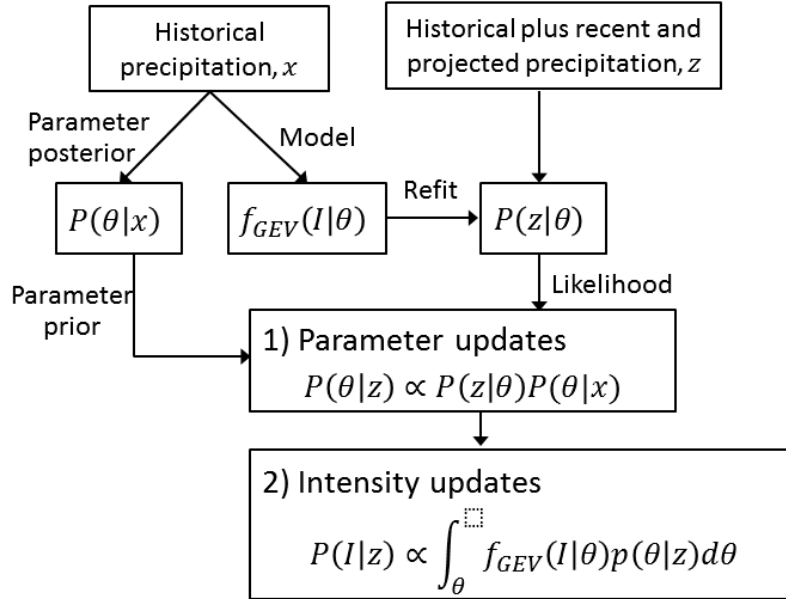


Figure 11. The Bayesian procedure to update the IDF curves using recently available precipitation data.

5.11.2. Non-stationary IDF Curves

Following the extreme value theory (Coles 2001; Katz et al. 2002), the generalized extreme value (GEV) distribution was used to evaluate and develop the non-stationarity IDF curves. For annual maximum precipitation series (X) under a no-trend assumption, the GEV model (M_0) can be formalized as follow:

$$M_0: X \sim GEV(\mu, \sigma, \xi) \quad 15$$

where the location (μ), scale(σ), and shape (ξ) are considered to be constant overtime. For the non-stationary case (i.e. independent but non-identically distributed random values), the type of distribution is commonly assumed to remain the same over time, while the distribution parameters vary as a function of time or other explanatory variables (also known as covariates) which also may vary with time. Consequently, the stationary distributions can be easily extended to nonstationary distributions (M_1) whose parameters are not constant but change as a function of a covariate (e.g., Coles 2001, Strupczewski and Kaczmarek 2001, Katz et al. 2002, Ouarda and El-Adlouni, 2011; Renard et al. 2006; Renard et al. 2013, Sugahara et al. 2009, Cheng et al. 2014). In this project, the location parameter was changed as a linear function of various covariances including time to develop the nonstationary GEV model (M_1):

$$M_1: X \sim GEV(\mu_c, \sigma, \xi) \quad 16$$

Where:

$$\mu_c = \mu_0 + \mu_1 c$$

where c is the covariate and the slope parameter μ_1 represents the trend or the level of non-stationarity. The covariate was selected by comparing the performance of the stationary and non-stationary GEV distributions using the different covariates.

The return period is typically defined as the waiting time for a given storm to be exceeded for the first time (Olsen et al. 1998). For stationary events, the probability of a particular storm event (or return level) to be exceeded is the same for all years, leading to a constant average return period which is calculated as the inverse of the probability of exceedance. There is thus a one-to-one relationship between return period and return level for stationary events (Cooley 2013). While for the non-stationarity events, the return period of a given storm event and the corresponding probability of exceedance vary as a function of time and/or covariates. Consequently, the return period is not only dependent on the return level but also affected by the time used for the analysis. For nonstationary events with an increasing trend, the probability of exceedance is initially low but increases over the years. Determining the return periods for practical engineering design is, in fact, the main challenge in adopting the nonstationary frequency analysis as both the return periods and levels changes depending on the time of the analysis and even more challenging if the return periods vary with other covariates.

In order to get a one-to-one relationship between return periods and return levels under a nonstationary condition for constructing the IDF curves, Cooley (2013) and Salas and Obeysekera (2014) extended the average return period concept from stationary cases to non-stationary cases.

We have adopted those methodologies to determine the return period and level under nonstationary extreme precipitations.

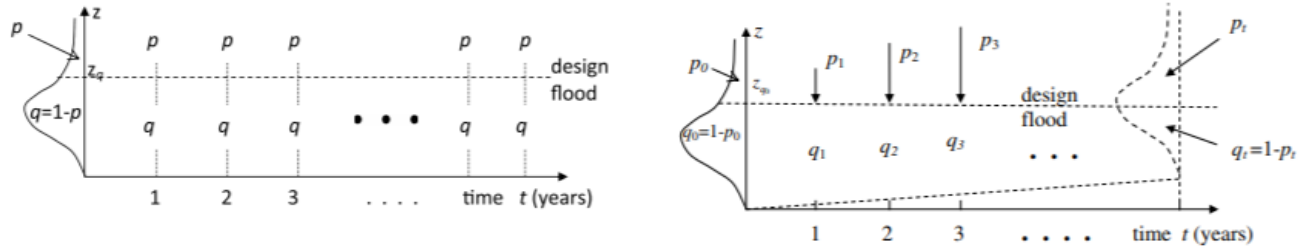


Figure 12. Schematic representation of the return levels and periods (probability of exceedances) for stationary and nonstationary frequency analysis (adopted from Salas and Obeysekera, 2014).

As shown in Figure 12 above, the exceedance probability p for any particular (or design) storm z_p remains constant year to year for the stationary case. Assuming that the annual maximum precipitations X are independent. The waiting time required for the storm event z_p to be exceeded for the first time is a random variable that can be described using a geometric distribution. The expected value of the waiting time, which is also known as the return period T , is computed using:

$$T = E(X) = \sum_{x=1}^{\infty} xp(1-p)^{x-1} = \frac{1}{p} \quad 17$$

Furthermore, the variance of the return period is $Var(T) = \frac{1-p}{p^2}$. These are well known statistics to characterize return periods for a stationary and independent annual maximum series.

Cooley (2013) and Salas and Obeysekera (2014) have extended the above relationships for non-stationary cases where unlike to the stationary case, the probability of exceedance p_t vary with time. For an increasing trend, the probability of exceedance p_t also increases over time. Similar to the stationary case, under independent extreme precipitation time series, the waiting time required for the storm event z_p to be exceeded for the first time is a random variable that can be described using a geometric distribution. The expected time for the first exceedance (or return period T) is computed using:

$$T = E(X) = 1 + \sum_{x=1}^{x_{max}} \prod_{t=1}^x (1-p_t) \quad 18$$

The above equation can be used to estimate the return period T for nonstationary conditions with increasing trend. If the trend is negative, the return period can be calculated using:

$$T = E(X) = \sum_{x=1}^{\infty} xp_x \prod_{t=1}^{x-1} (1-p_t) \quad 19$$

where p_x is exceedance probability at $t = x$, x_{max} is the year at which $p_x = 1$ or the year that the design storm will definitely be exceeded. This condition is possible when we have increasing trend in annual maximum precipitation that leads to increasing probability of exceedance with a potential to reach one. The return periods from stationary (Equation 3) and nonstationary (Equations 4 and 5) can be directly compared to assess the impact of non-stationarity on IDF curves and associated engineering design and flooding risk. Alternatively, the average return period is computed using different quantiles to estimate the corresponding distribution parameter, $\mu(t)$ and $\sigma(t)$. For example, Cheng et al (2014) used median of $\mu(t)$ to determine the “effective” return level for the year corresponding to the midpoint of the historical time series. For the low risk design, the 95 percentiles of the $\mu(t)$ values is used. The effective return period can also be used if covariates other than time were used to represent the nonstationarity in the IDF curves.

For nonstationary condition, the risk of failure of the hydraulic structure having design life n was determined using: (Salas and Obeysekera 2014)

$$R = \sum_{x=1}^n p_x \prod_{t=1}^{x-1} (1 - p_t) = 1 - \prod_{t=1}^n (1 - p_t) \quad 19$$

The above equation can be reduced to the well-known equation of the risk of failure, $R = 1 - (1 - p)^n$, for stationary condition with a constant p value.

5.12. Runoff IDF Curves

Even though the design risk levels for flooding and stormwater infrastructures are often defined through the return period and associated intensity of heavy rainfall events, the actual probabilities of occurrence of flooding and associated risk levels for design and operation of infrastructures are directly related to runoff, which are also strongly depends on drainage characteristics, including land cover, soil type, topography, and river network. However, due to the lack of historical and future streamflow data for flood frequency analysis at or near most drainage sites, it is a common practice to directly estimate the design flood (maximum discharge or volume of stream for a given return period) based on storm frequency analysis and the resulted rainfall IDF curves. Such analysis assumes a direct relationship between storms and floods with, for example, a 10-year rainfall expected to produce a 10-year flood. However, in reality, a storm is just one factor among the many other hydrological and metrological factors that can affect the peak flow and hydrograph. Consequently, a heavy storm does not necessarily always lead to flooding or a flood events with the same frequency. This is evident by the observed difference in the seasonality of heavy storms and floods in most regions (see details in the result section).

The watershed, storm and flood data were analyzed in order to identify the underlying causes of historical floods at and near the 13 military installations. The results from the analysis will be used to guide the use of the rainfall IDF curves for flood frequency analysis and flood mapping. If a given installation is often affected by flash floods, the storm information from the rainfall IDF curves can be directly used, without the need for soil moisture condition information, to estimate the associated flood. The commonly applied Rational Method or the Hydrologic Engineering

Center – Hydrologic Modeling System (HEC-HMS) model (USACE 2010) with the SCS runoff estimation method can be used to simulate flash floods. On the other hand, for those installations that are commonly affected by the riverine floods and floods caused by storm over saturated soil or snowmelt, the storm information from the rainfall IDF curves is not sufficient to estimate the level of floods. Physically based hydrologic model, such as HEC-HMS with Soil Moisture Accounting (SMA), are needed to take into account the antecedent soil moisture. The accuracy of the flood frequency analysis and the resulted runoff IDF curves will be evaluated based on the runoff IDF curves developed from streamflow measurements.

The HEC-HMS model uses a design storm (or rainfall intensity and duration for a given return period) derived from the rainfall IDF curves along with a readily available watershed data (e.g. soil, land cover, and digital elevation map) to estimate the runoff hydrograph. The model was chosen for this project due to its ability (1) to simulate the peak discharge and hydrograph from multiple spatially and temporally varying storm events in a large basin with various drainage characteristics, (2) to simulate the effects of snowmelt and accumulation on the hydrograph, (3) to compute runoff and flood routing using a variety of modeling options. The Hydrologic Engineering Center – River Analysis System (HEC-RAS) will use the estimated hydrograph from the HEC-HMS model and information related the channel cross-sections to estimate the floodplain inundation. Finally, the Storm Water Management Model (SWMM) will be coupled with the HEC-HMS model to assess the capacity of existing stormwater drainage system at the military installations and provide recommendations.

5.13. Snowmelt Modeling

Runoff from snowmelt and rainfall over snow cover is associated with a significant flood hazard in many parts of the United States. Although this significant effect of snow on flooding, the existing rainfall IDF curves and the runoff frequency analysis often fail to consider effects of snowpack, snowmelt, timing, and coincidence with heavy rainfall.

In this project, we used the Utah Energy Balance (UEB) snowmelt model (Tarboton et al. 1995; Mahat and Tarboton 2012) to understand better the runoff behavior associated with snowmelt and rain-on-snow events. The UEB is a process-based model that accounts for exchanges of air temperature, fluxes of energy due to incoming and outgoing short- and long-wave radiation, thermal or heat conduction, evaporation and condensation, and horizontal heat transport to calculate snow accumulation and snowmelt. The UEB model was driven by air temperature, precipitation, wind speed, humidity, and radiation inputs at an hourly time scale. The model output of snow water equivalent (SWE: the amount of water contained within the snowpack if it were all melted without evaporation) was compared with the observed SWE for multiple locations in each of sites where observed SWE data were available. The comparison showed that the modeled SWE agreed with the observed SWE, indicating its ability to capture the snowmelt processes. The hourly snowmelt projections from the UEB model was combined with precipitation to form the total amount of water that contributes to the surface runoff. The combined datasets were used to re-extract annual maximum series for developing IDF curves.

UEB has been used in various hydrological studies including estimating snow and glacier melt in the high Himalayas (Brown et al., 2014), analyzing potential climate change impacts in

Sacramento/San Joaquin watershed (Knowles and Cayan, 2002), and assessing the surface meteorological variables most critical for snowmelt (Raleigh et al., 2008). See Tarboton et al., 1995 or Mahat & Tarbotan, 2012; 2013 and Mahat et al., 2013 for detailed description and functionality of the UEB model.

5.14. Geodatabase and Web-based GIS Tool

A Geographic Information System (GIS) geodatabase was developed, and populated with the study results for the planned geographic regions and climate scenarios, and a project website and web-based mapping tool were created to provide access to the results. In preparation for populating the geodatabase, IDF analysis results were stored in data files for each combination of site location, station or grid, historical or future projected, and rainfall or rainfall with snow melting. These files are also downloadable from the project website at the request. Python code parsed data files and loaded the IDF data into PostGIS, an open source spatial database built on PostgreSQL. Each station and grid cell had the IDF stored as a multi-dimensional array for efficient data access.

An associated web-based GIS tool was also developed to provide an accessible and easily understandable way to access results. The interface includes menu-based selection of which results to display, a map panel displaying the results in their geographic context, and a graph and table panel to display IDF data. To provide context for the mapping tool, a project website was developed with a brief project summary, description of the web-based tool with a link to launch it, a news section with announcements about project activities, help content for the tool, and links to download IDF data files this report, and related manuscripts from this project.

A number of open-source software components were used to build the system to provide the needed functionality without licensing costs. These components include the Ubuntu/Linux operating system, PostgreSQL and PostGIS for geospatial data management, GeoServer for web-based geospatial visualization and data access services, and OpenLayers for map display and interaction in the browser. To facilitate use of the web-based application and provide contextual information, the site will include instructive text and brief videos, descriptions of the methodology, and other supporting information as needed. After the site has been launched and the proposed project schedule is completed, related programmatic activities can provide for continued hosting and maintenance of the site into the future.

6. RESULTS AND DISCUSSION

6.1. Trends in Magnitude and Frequency of Extreme Precipitations

We have conducted trend analysis using annual maximum precipitation data from all the stations located near the installations and with more than 30 years complete records and using representative long-term precipitations data obtained by combining data from nearby stations. In the first case, the Mann Kendall (MK) test was used to evaluate trends at each station, while in the second case the likelihood ratio between stationary probability distributions and non-stationary probability distributions, with linear trend in the location parameters, were used to evaluate long-term trends and non-stationary in the annual maximum precipitation. The results from the MK test are

presented in this section, while the results from the likelihood ratio test are discussed in section 6.8.

The percentage of stations showing significant trends in the annual maximum precipitations with durations ranging from 1-hour to 10-day are shown in Figure 13. Relatively more stations (10%-16%) showed increasing trend than decreasing trend (4%-6%) in the past, particularly those stations located in the Midwest (Ft. McCoy and Ft. Riley) and Northeast (Ft. Drum and Aberdeen PG). The increasing trend is relatively higher for daily and longer durations storms with some exception for the southern installations and Lewis McChord, which show more stations with increasing trends in sub-daily storms. Relative to the other installations, Ft. McCoy has experienced more increasing trends in daily and longer durations storms.

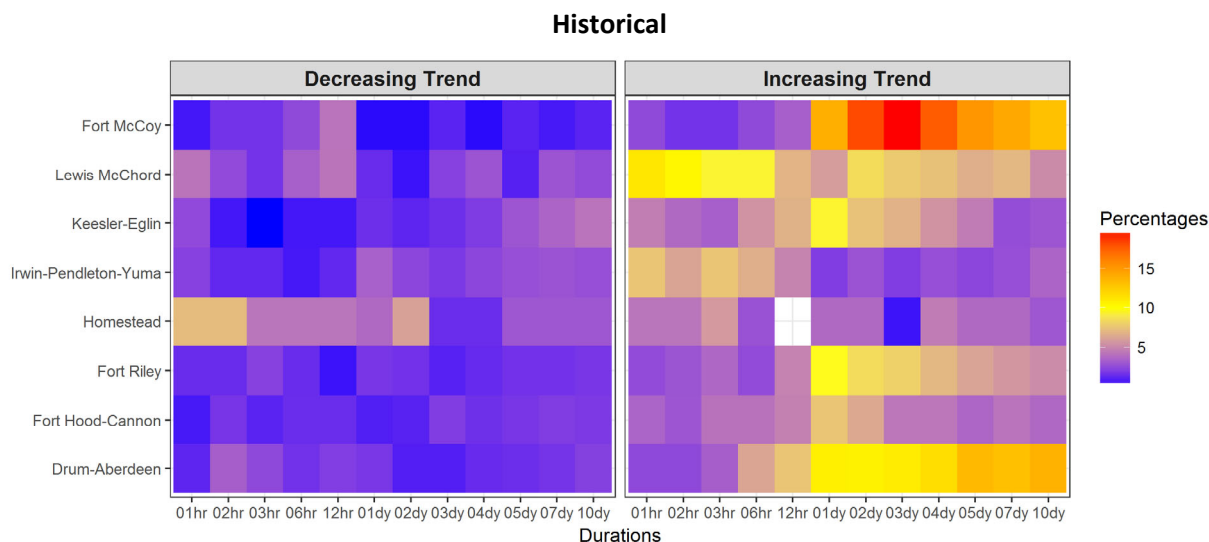


Figure 13. Percentage of stations showing statistically significant increasing and decreasing trends in the annual maximum precipitations using the past data

The future projections based on the CCSM and GFDL models under RCP 8.5 scenario showed an overall increasing trend in daily and longer durations storms while a decreasing trend in sub-daily storms magnitudes at majority of the installations (Figure 14). The only exceptions are the southwestern installations and Homestead ARB, where most of the stations showed decreasing trends for all durations of the storms. Similar trends (i.e., increasing trend in long durations storm and decreasing trends in short durations storm) were observed under the RCP 4.5 emission scenario. The decreasing trend in sub-daily storm magnitude is consistent for all the installations and emission scenarios we have considered, with close to 100% of stations in the southern installations showing significantly decreasing trend in the future. Compared to the observed changes in storm magnitudes over the past century, large number of stations showed significantly increasing trends for daily and longer durations storms while decreasing trends for sub-daily durations storm under both the RCP 8.5 and 4.5 scenarios. These likely future trends in annual maximum precipitations underscore the need for non-stationary frequency analysis to represent the effects of climate change on IDF curves and corresponding engineering applications.

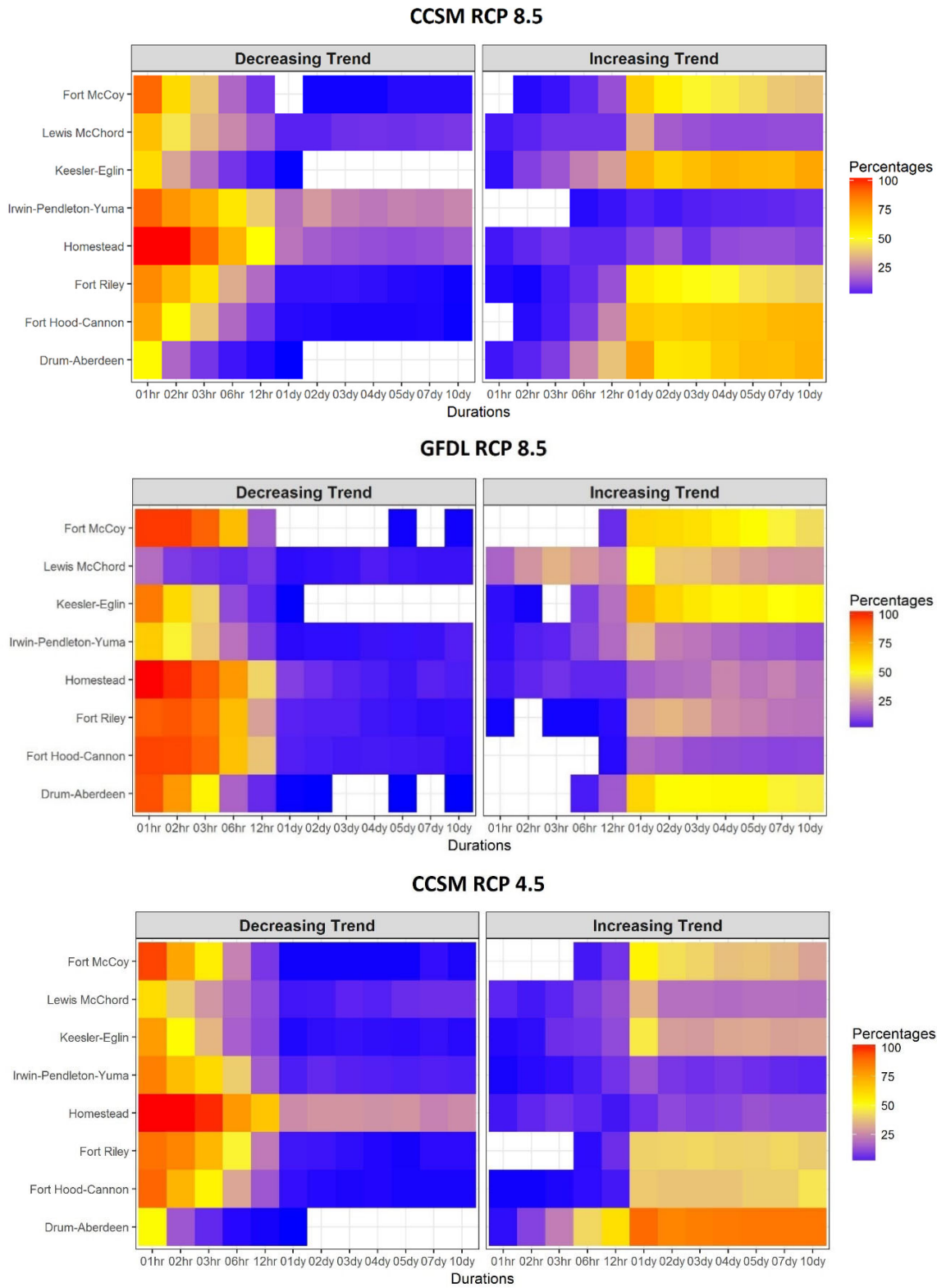


Figure 14. Percentage of stations showing statistically significant increasing and decreasing trends in the annual maximum precipitations using the combined past and future data.

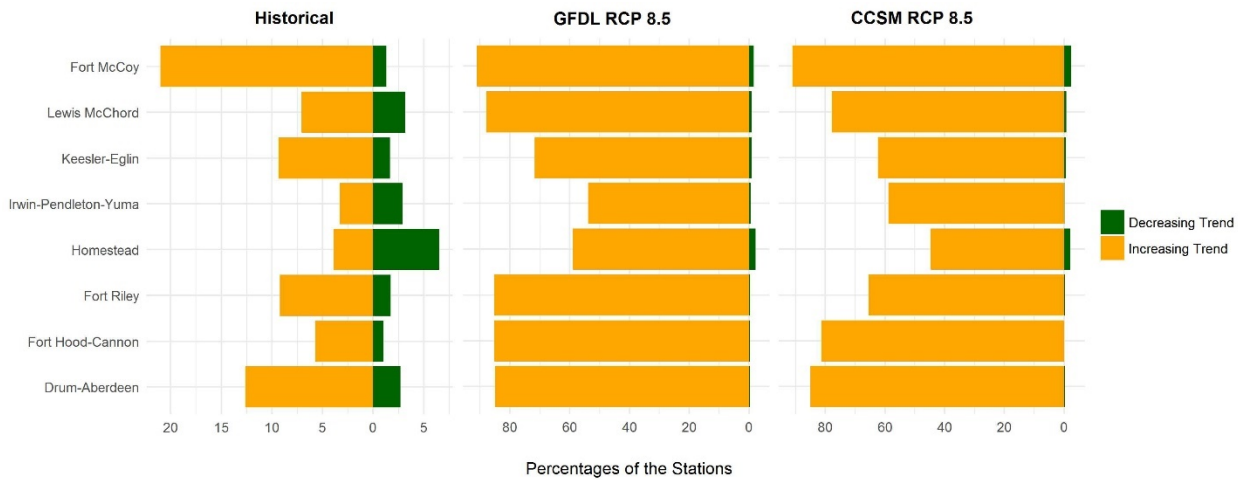


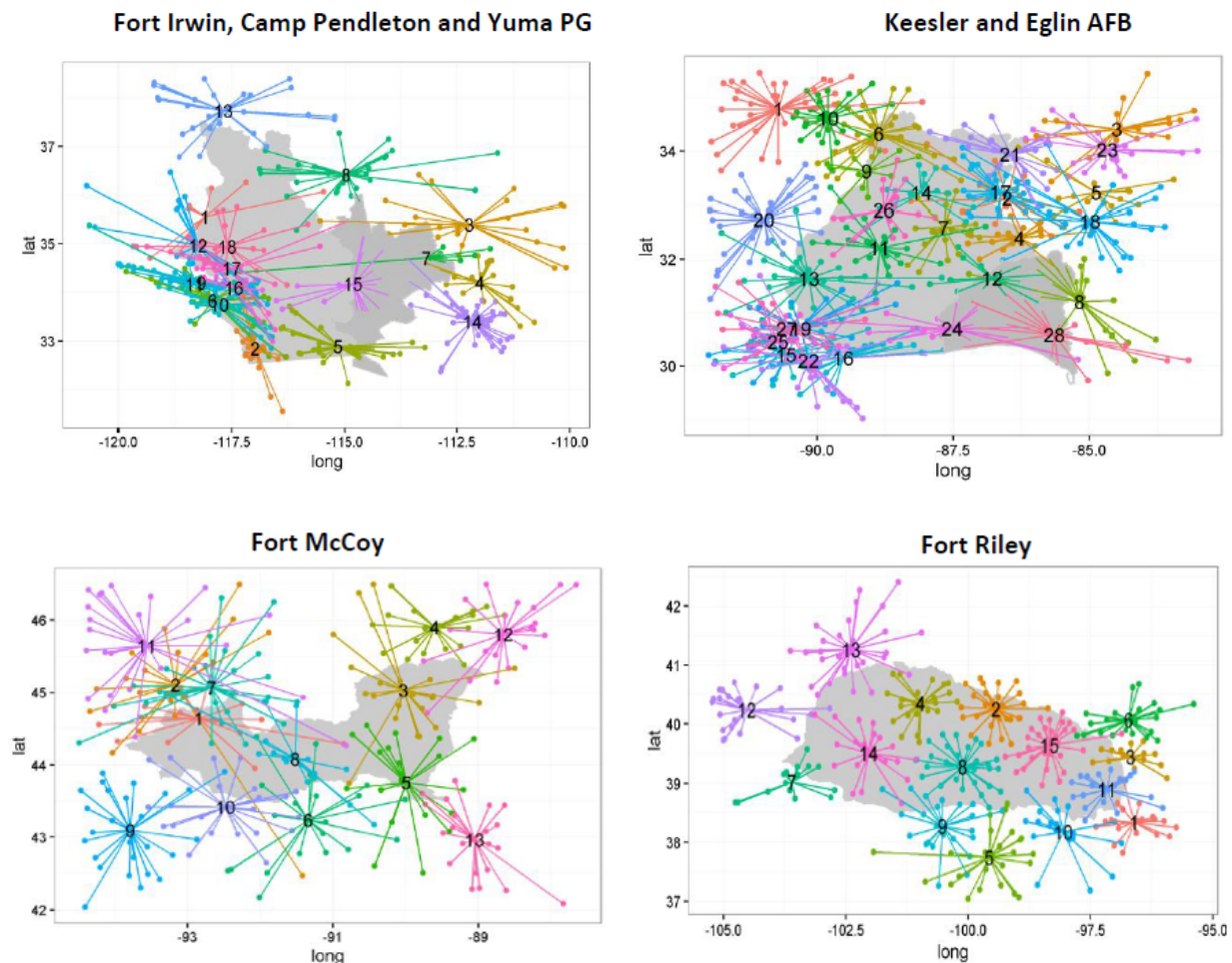
Figure 15. Percentage of stations showing statistically significant increasing and decreasing trends in the number of heaviest (1%) daily precipitation.

In addition to the annual maximum precipitation, we have used the daily precipitation that has a 1% chance to occur on any given day to examine the potential trend in storm frequency (Figure 15). In the past, more stations (4%-20%) showed increasing trend in the frequency of the 1% precipitations, while relatively few stations (1%-6%) showed decreasing trends in the frequency of the 1% precipitations. For instant, 20% of the stations in Ft. McCoy area showed increased trend in the frequency compared to about only 1% of the stations which showed a decreasing trend. The increasing trend in the storm frequency is expected to be more pronounced and consistent across all the installations and climate model projections in the future, with about 50% to 90% of the stations showing increased frequency of storm. Despite this observed increasing and decreasing trends at some of the stations, regionalized historical precipitation data didn't show significant trends.

6.2. Climatological Homogeneous Regions

The purpose of this task is to form groups of stations that have climatologically homogeneity condition, whereby, apart from station-specific scale factors, the extreme precipitations at stations within a homogeneous region can be characterized by identical frequency distributions. The grouping of stations involves two main steps: (1) identifying initial regions based on site characteristics such as latitude, longitude, elevation, and mean annual precipitation, and (2) refining the regions by moving around discordant stations from one region to another till all the regions satisfies the homogeneity statistics (H statistics). In this project, instead of deterministic initial grouping, which assumes a given station to belong to a region 100% and does not belong to any other regions, stochastic initial grouping that assumes a given station to belong to a various region with certain probabilities, were prepared using a fuzzy clustering technique. The probability information is critical during the refinement of the regions since it effectively and automatically guides the movement of discordant stations. In addition, unlike other similar studies, the regionalization was conducted for each storm duration considered, allowing for delineation of

different regions for different durations of the storms. Figure 16 shows the final regions for one-day extreme precipitations in regions near to the 13 military installations. The figures show that the one day storms are more localized in the interior regions of the US (e.g. Fort Riley, Fort Hood and Cannon AFB), while they are more spread in the coastal regions of the US (Lewis-McChord, Camp Pendleton and Homestead AFB). This is expected based on the common metrological drivers responsible for major storms in the different parts of the US. The extreme storms in the Midwest and the southern US are often associated with convective thunderstorm which impacts relatively small areas, while the coastal regions are affected by frontal storms and hurricane that can affect relatively wider areas.



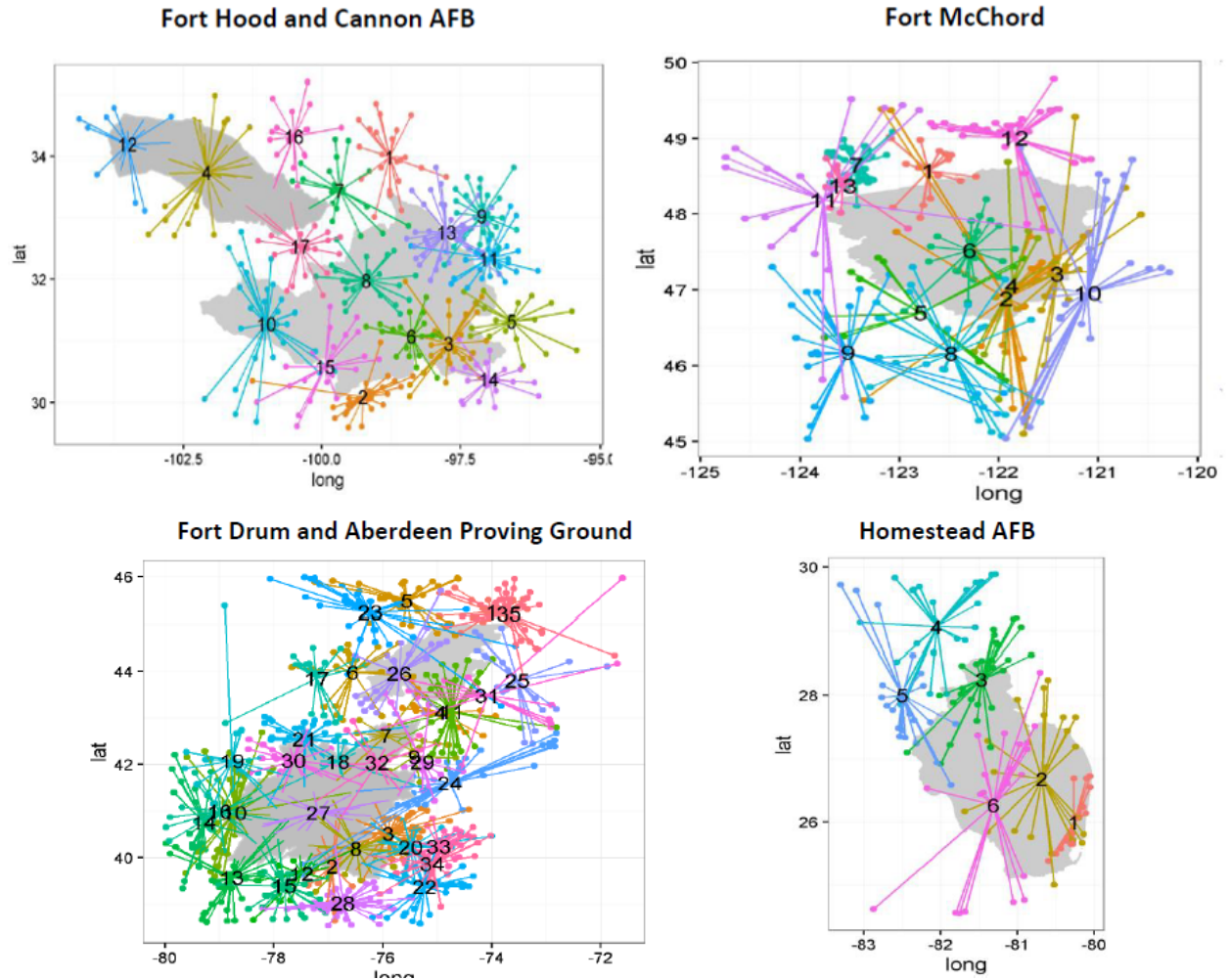


Figure 16. Homogeneous regions for the one-day extreme precipitations in the 13 military installations.

6.3. Regional Probability Distributions

In the standard regional frequency analysis, a single frequency distribution is fitted to the data from several sites in a homogeneous region. Because the “true” distribution of extreme rainfall is not known, a distribution must be chosen that not only provides a good fit to the data but will also yield robust and accurate quantile estimates for each site in the region. In order to accomplish this modeling objection and incorporate uncertainty in selecting a distribution into the estimated quantiles, we have adopted a Bayesian Model Averaging approach which allows selecting multiple appropriate distributions that fit the data reasonably well. The bar graphs in Figure 17 showed the multiple distributions selected for each duration and region. The y-axis represents the number of homogeneous regions that use a given combinations of distributions. For example, for the 1-day storm events in the Lewis-McChord area: (1) we have identified 24 homogeneous regions of which

GLO is rank 1 distribution for the 2 regions while GEV is rank 1 for 18 regions; (2) out of the 24 regions, only 16 regions have second or rank 2 distributions that met the Z-statistics criteria for selecting candidate distributions, while for the remaining 8 regions only a single distribution met the criteria and the BMA was not required for those regions; (3) out of the 24 regions only 6 regions have a third or rank 3 distributions for the BMA application. Overall, the GEV distribution was identified as the most suitable distribution to describe the extreme precipitations at both installations.



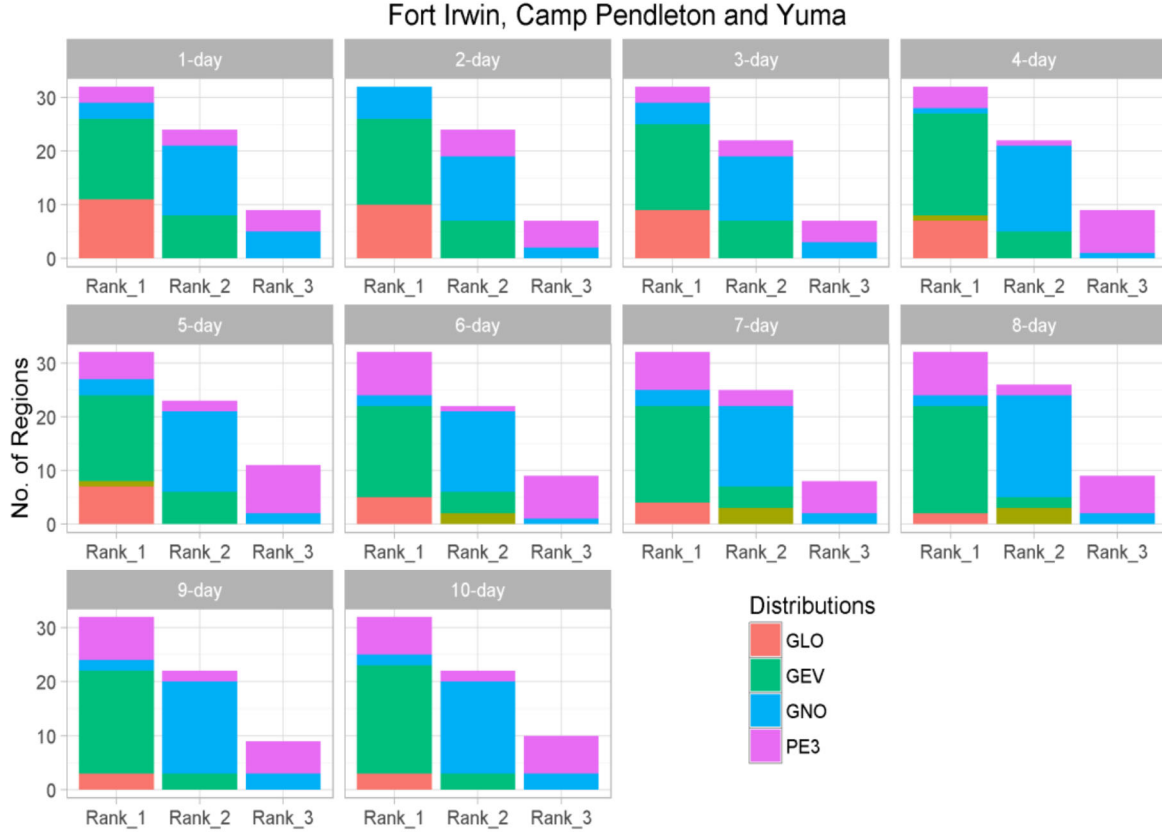


Figure 17. Percentage of the top three best-fit distributions based on the Z-statistics for different climatologically homogeneous regions and storm duration from 1 to 10 days.

6.4. Parameter Estimation

Bayesian parameter estimation method was used to estimate the parameters of the selected distributions. To demonstrate the parameter uncertainties and their effect on the precipitation frequency analysis, we have included Figures 18 and 19 which show the estimated parameters and associated uncertainty ranges on the estimate IDF curves, respectively. The figures reveal the need for not only estimating the optimal parameters values, but also quantifying the associated uncertainties. Even if the IDF curve results using the optimal parameters might fail to capture the highest extreme precipitations, the estimated parameter and model uncertainty confidence intervals are able to encompass those precipitations events, providing reliable ranges of the precipitation estimates.

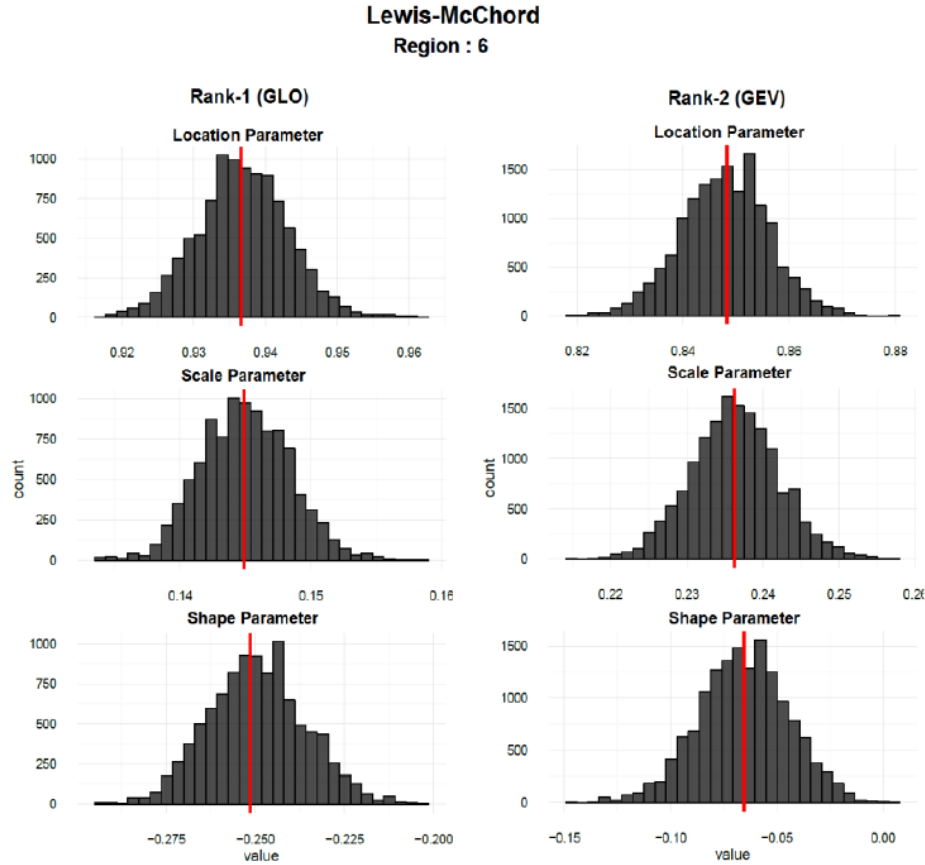


Figure 18. The posterior distributions of the GLO and GEV distributions used to describe the daily storms for a homogeneous region near Lewis-McChord. The red vertical lines in the parameter distributions indicate the maximum a posteriori estimate (MAP) which is also commonly referred as the optimum value of a parameter. The MAP values were used for developing the IDF curves while the rest of the parameter values were used for the confidence intervals.

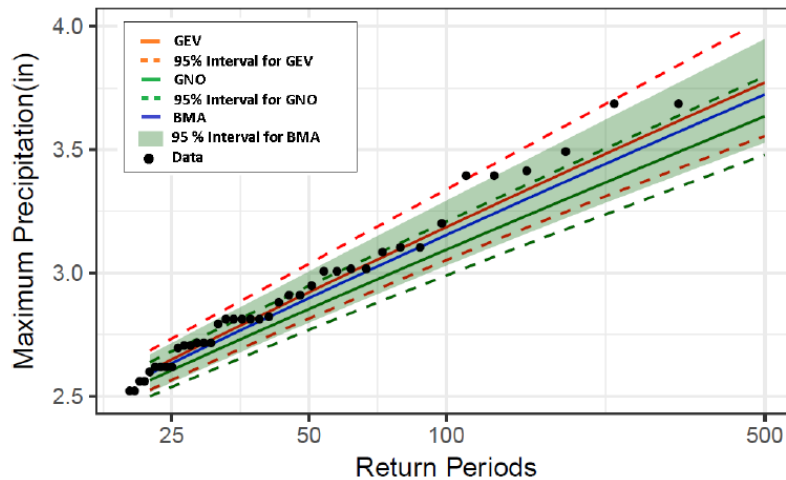


Figure 19. The IDF curve and associated 95% confidence intervals for one day storms for a weather station near to the Lewis-McChord. The different confidence intervals in the figure are related to parameter and distribution selection uncertainties.

6.5. Stationary IDF Curves

The rainfall IDF curves covering storm durations from 1-hour to 10-day and return periods from 2-year to 500-year were developed for all the installations using currently available (or historical) precipitation records. Figure 20 shows the IDF curves for representative weather stations at each installation. As is typical with IDF curves, the precipitation amounts, express in inch, are highest at longer averaging durations. For both installations, the variations in the precipitation amounts as a function of return periods are smaller for shorter durations than longer durations, indicating the relatively minor role of return periods play on engineering designs that handles precipitations with shorter durations. As discussed earlier, the station-based IDF curves were derived by multiplying the regional IDF curves using station specific scaling factors. Bilinear interpolations were used to get monotonic IDF curves. For all the other weather stations and different IDF curve formats (e.g. precipitation vs frequency or duration), as well as for the actual data, please refer to the project website (<https://bogi.evs.anl.gov/dodewa/tool/index.html>).

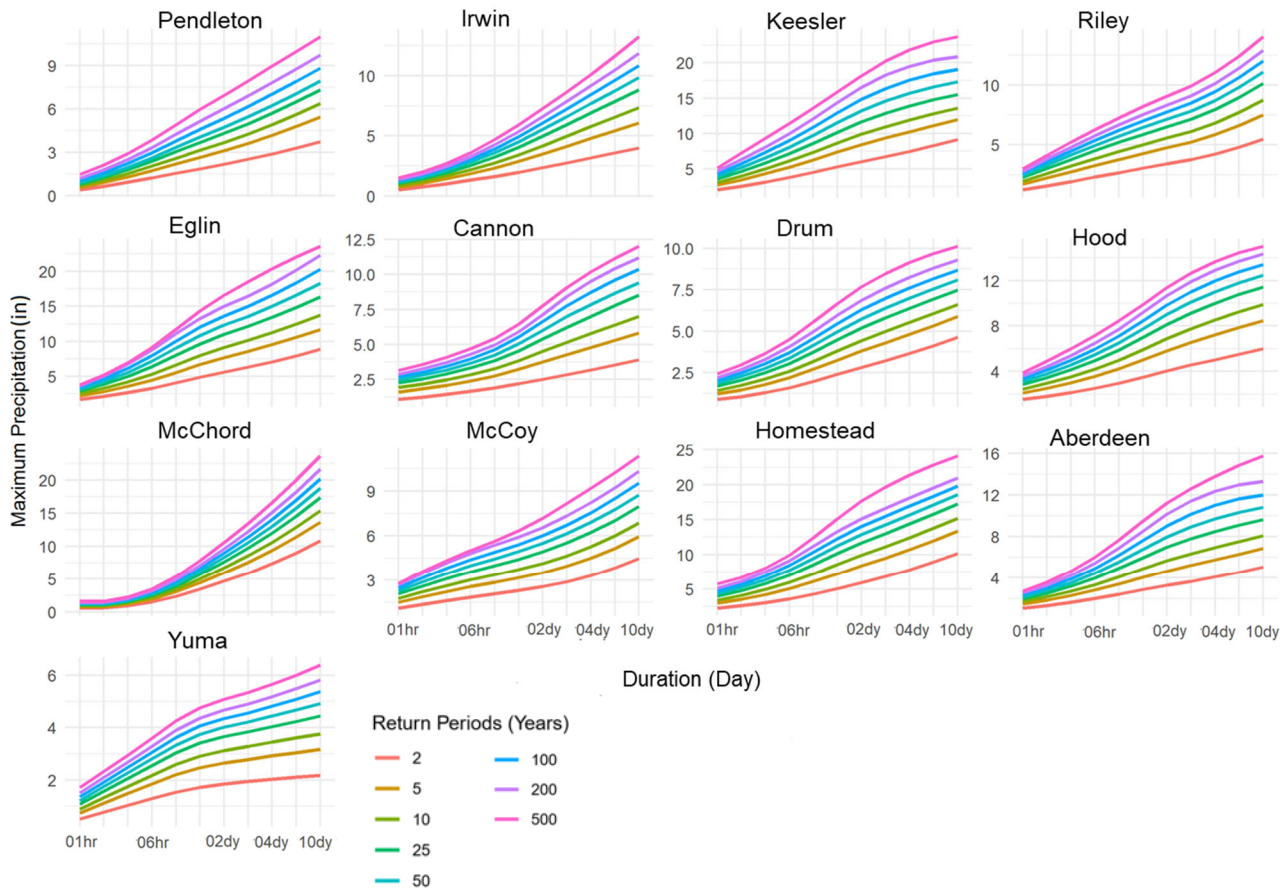


Figure 20. Stationary IDF curves for representative stations corresponding to the military installations.

Figure 21 illustrates the IDF curves and associated confidence interval representing the uncertainties related to model selection and estimation of their parameters. The project website provides the IDF curves and the corresponding confidence intervals for all the weather stations and return periods. Overall, the resulted mean IDF curves, derived from expected values of the posterior distributions, are in good agreement with both the NOAA and observed IDF values (not show here). The IDF curves available from the NOAA involve fitting a representative distribution to observed historical extreme precipitation, while in our case, a Bayesian approach was used to construct the IDF curves by combining different distributions. For some of the installations, such as Fort Drum and Fort McCoy, the IDF values from this project tend to match the observed values better than the NOAA estimates. As expected, the uncertainty range is wider for the IDF curves corresponding to higher return periods than lower return periods.

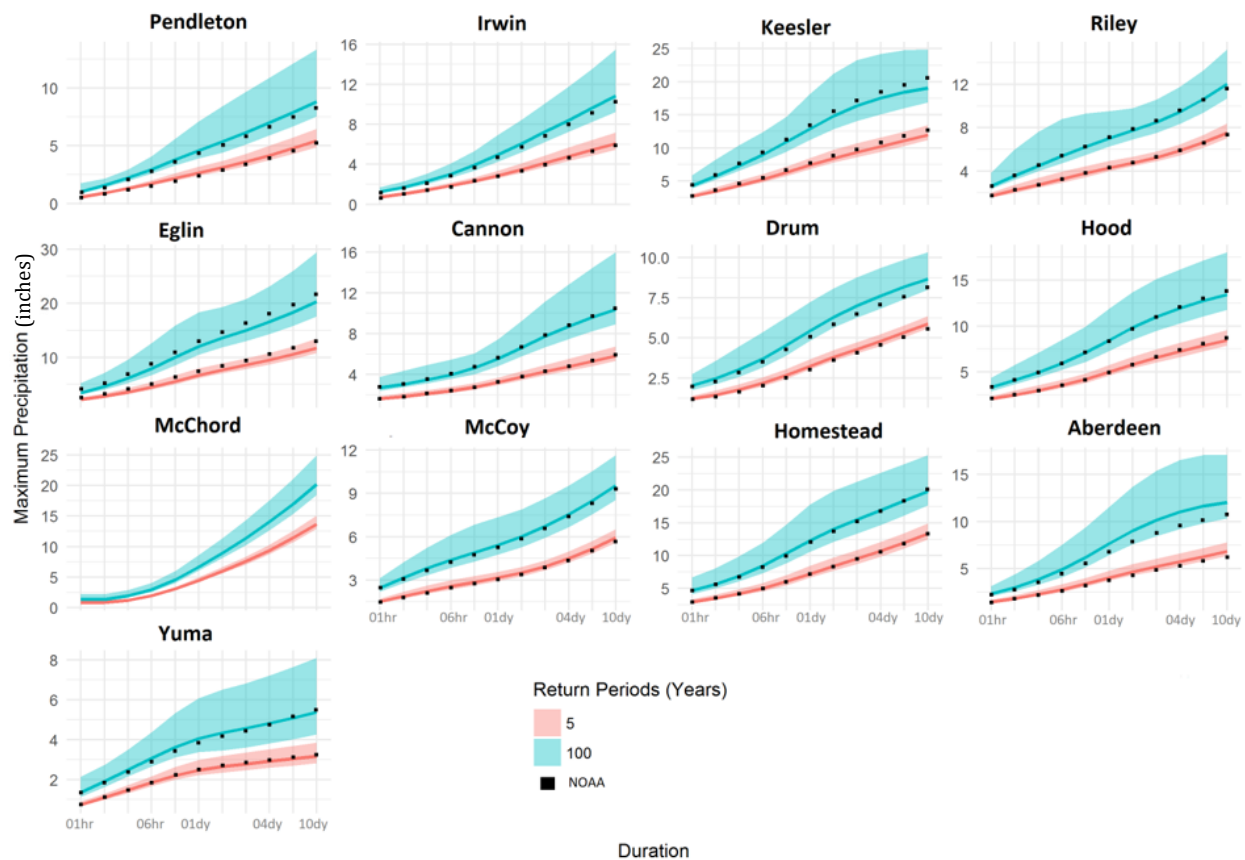


Figure 21. Stationary IDF curves for 5-yr and 100-yr return periods and associated 95% confidence intervals considering parameter and model uncertainties. The dots are the estimates from the NOAA Atlas for comparison.

6.6. Downscaled and Bias-Corrected Climate Projections

The bias correction method, HQM, developed in this project represents an improvement by correcting extreme precipitations (top 1%) with extreme value theory and precipitations below 99% with modified quantile mapping. The performance evaluation suggest it improves both annual

maximum series based on corrected top 1 % precipitations and mean seasonal or monthly values from corrected 99% precipitations. Figure 22 shows the mean of the annual maximums (in.) at each grid cell for each watershed based on observed, uncorrected CCSM 8.5 RCM, and corrected CCSM 8.5 RCM data. The bias corrected mean of the annual maximums series is consistent with the observed AMS. In addition, bias corrected AMS also preserves the signals of change in extreme precipitation projected in the WRF-RCM from historical to future periods as shown in Figure 22. The percent difference (%) in the mean annual maximum from historical (1975-2004) to future (2035-2064) period is consistent and well maintained before and after bias corrections.

The bias correction for the majority precipitation (99%) is also performed well. Figure 23 shows mean monthly total precipitations of observed, modeled, and bias corrected modeled datasets over the same historical period (1981-2004). The significant deviation of the modeled monthly precipitation from the observed data was corrected successfully and the corrected precipitations are well agreed with the observed data.

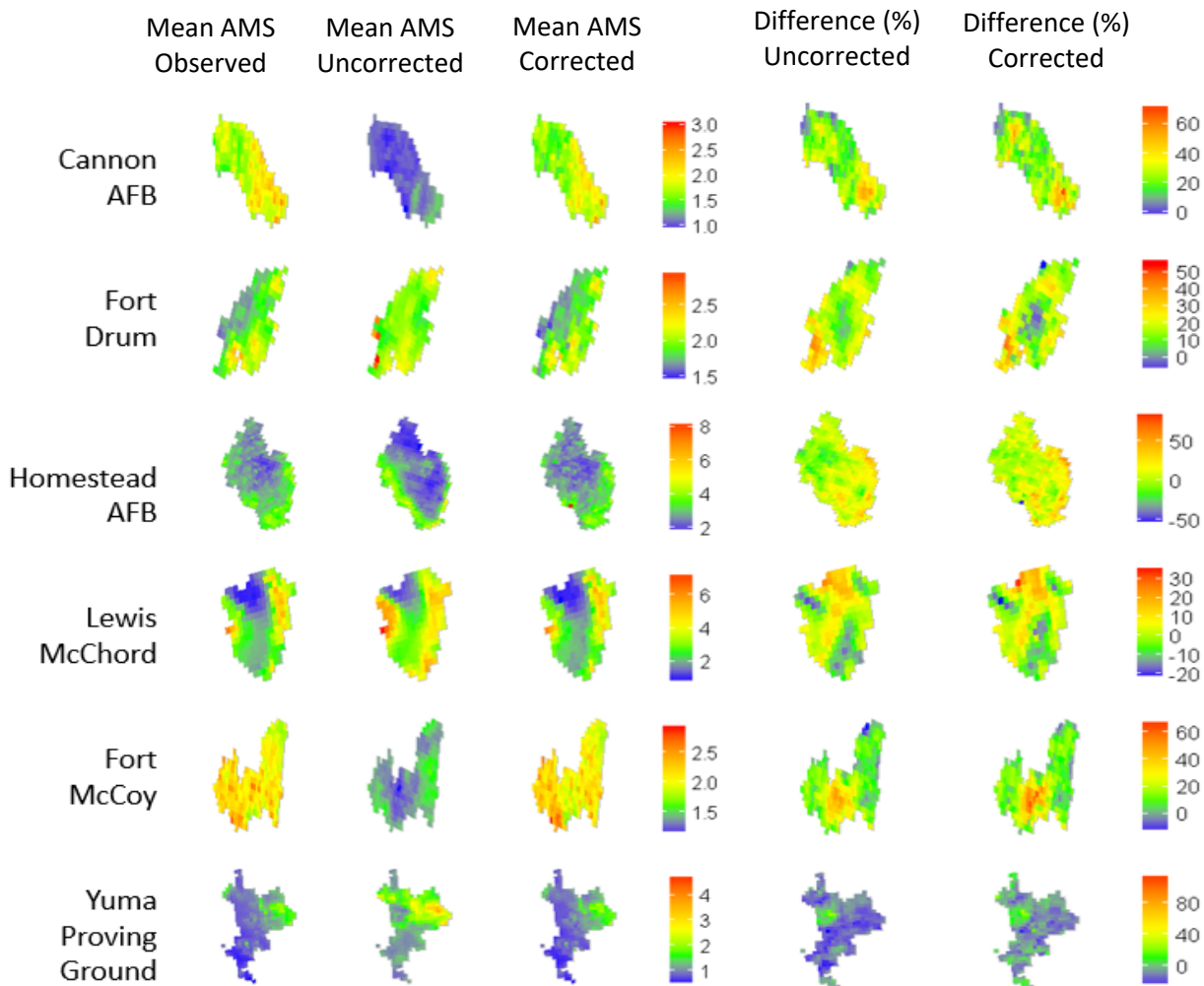


Figure 22. Comparison of mean annual maximum series (AMS) of observed, modeled (uncorrected), and bias-corrected precipitations (CCSM 8.5 WRF-RCM data) at six military bases.

The bias-corrected mean AMS agrees well with observed values at most of grids. The percent difference (%) in the mean annual maximum from historical (1975-2004) to future (2035-2064) periods for the uncorrected and corrected CCSM 8.5 WRF-RCM data. The change in AMS from historic to future projected in the model is well preserved after bias corrections.

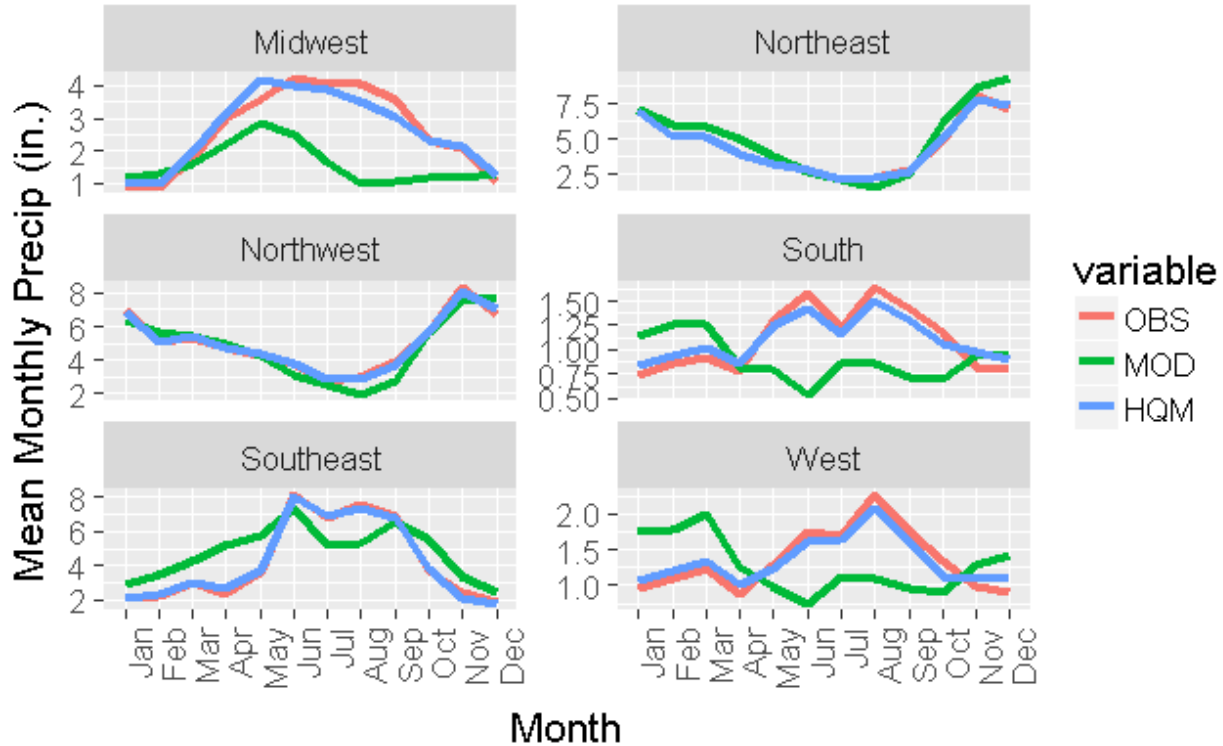


Figure 23. Mean monthly total precipitations for observed (red-OBS), modeled (green-MOD), and HQM bias-corrected (blue-HQM) datasets in 1981-2004 for sites located in six climate regions. While the MOD data varies significantly from the observed data in several regions, HQM correction is able to improve the seasonal pattern of the data, shown in close overlap between red and blue lines.

6.7. Bayesian Update of IDF Curves

The Bayesian approach was tested to update the IDF curves whenever new precipitation records are available. The approach assumes that the underlying probability distribution remains the same while the distribution parameters might change when the new precipitation data is incorporated to update the IDF curves. This assumption is reasonable for frequent update of the IDF curves and when no major change or shift in storm patterns are expected due to the assimilation of the new data. Figure 24 illustrates the effectiveness of the Bayesian data assimilation to update the IDF curves developed using precipitation data prior to 1990 by precipitation data post 1990. As shown in the figure, the resulted IDF curves from the data assimilation were comparable with the IDF curves developed using the entire data. The updating method, thus, can be used to effectively incorporate new observational data without the need to reconstructed completely new IDF curves. Furthermore, the updated curves compared to the

original curves provide insight on the recent changes in storm patterns and on the IDF curves. The upward shift in the IDF curves for Eglin, Keesler, Homestead, and Drum indicate the recent increase in the annual maximum daily precipitation post 1990, while the downward shift for Cannon, Irwin, and Yuma indicate the decrease in the annual maximum daily precipitation post 1990. The changes are more noticeable for severe storms or storms with higher return periods.

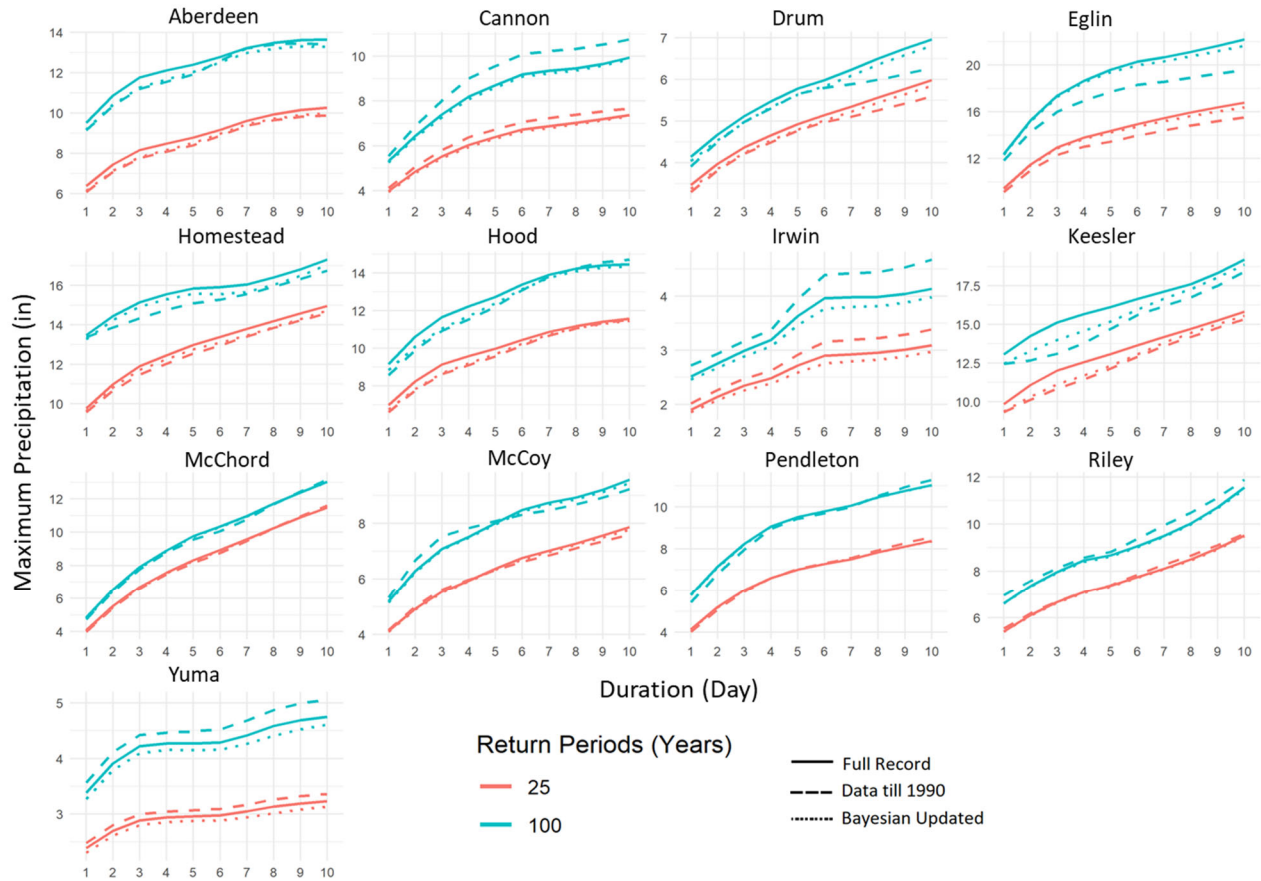


Figure 24. Bayesian update of the IDF curves for daily annual maximum precipitation using recently (post 1990) observed data.

6.8. Nonstationary IDF Curves

The influence of the different covariates on extreme precipitation is expected to vary from region to region. Thus, identifying those covariates which contribute to the nonstationarity patterns of the extreme precipitations at a given location is an important part of the nonstationary frequency analysis (e.g. Merz et al. 2012). We have considered time, annual precipitation, average minimum and maximum temperature and large-scale climate variability as covariates. The role of the different covariates on annual maximum precipitation were evaluated by comparing the performances of stationary and nonstationary GEV models with the location parameters being linearly related to the covariates (Figure 25). Using yearly precipitation as a covariate significantly improved the stationary GEV model for all the sites. On the other hand, the commonly used time

covariate has improved the stationary models for only two installations (Ft. Riley and Ft. Irwin). Except for the MEI, which improved the stationary models at four installations, the other large-scale climate variability showed little impact on the annual maximum precipitation. When the past and future data were combined, using the time covariates improved the stationary models for five installations. The annual average minimum and maximum temperatures have no significant relation with the annual maximum precipitation.

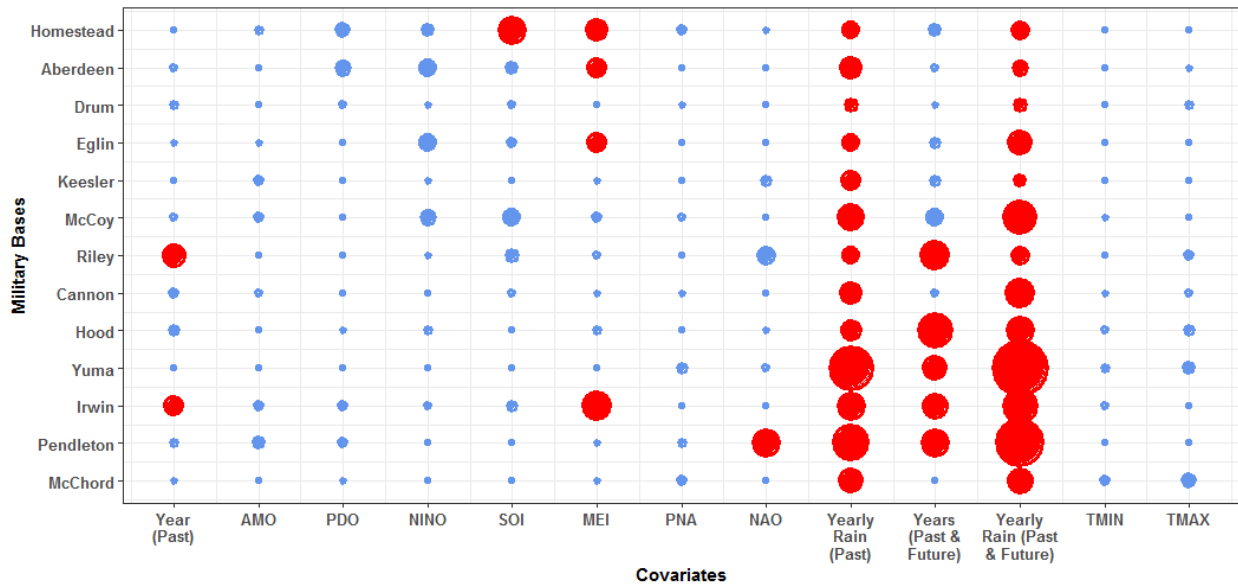


Figure 25. The influence of different covariates on the annual maximum precipitation. The circle represents the likelihood ratio between nonstationary and stationary GEV models, with red circle showing significant effect.

Figure 26 shows percentage difference between the stationary IDF curve using only the past precipitation record and nonstationary IDF values using the combined past and future precipitation data and time as a covariate. The CCSM model under RCP 8.5 was used for the future precipitation projection. The IDF values corresponding to longer durations increased for most of the installations with the increase being higher for the installations located in central and eastern part of the country. For the installations in the south and southwest, the nonstationary IDF values corresponding to sub-daily durations have decreased while they have increased for daily and longer durations. Alternatively, the impacts of non-stationarity storms could be posed as a design problem, in which case either the risk of failure or the return period is evaluated to compute the design flood capacity. Assuming that initially a project is designed to handle a certain amount of storm (design quantile) and return period, the exceedance probability with respect to this initial design quantile will increase (or decrease) with time due to the non-stationarity of the probability distribution. As a result, the frequency of the occurrences of exceeding the design quantile and causing failure will also increase (or decrease) with time. Such information is useful for planners and managers of infrastructure to assess the vulnerability of existing infrastructure under nonstationary storm conditions.

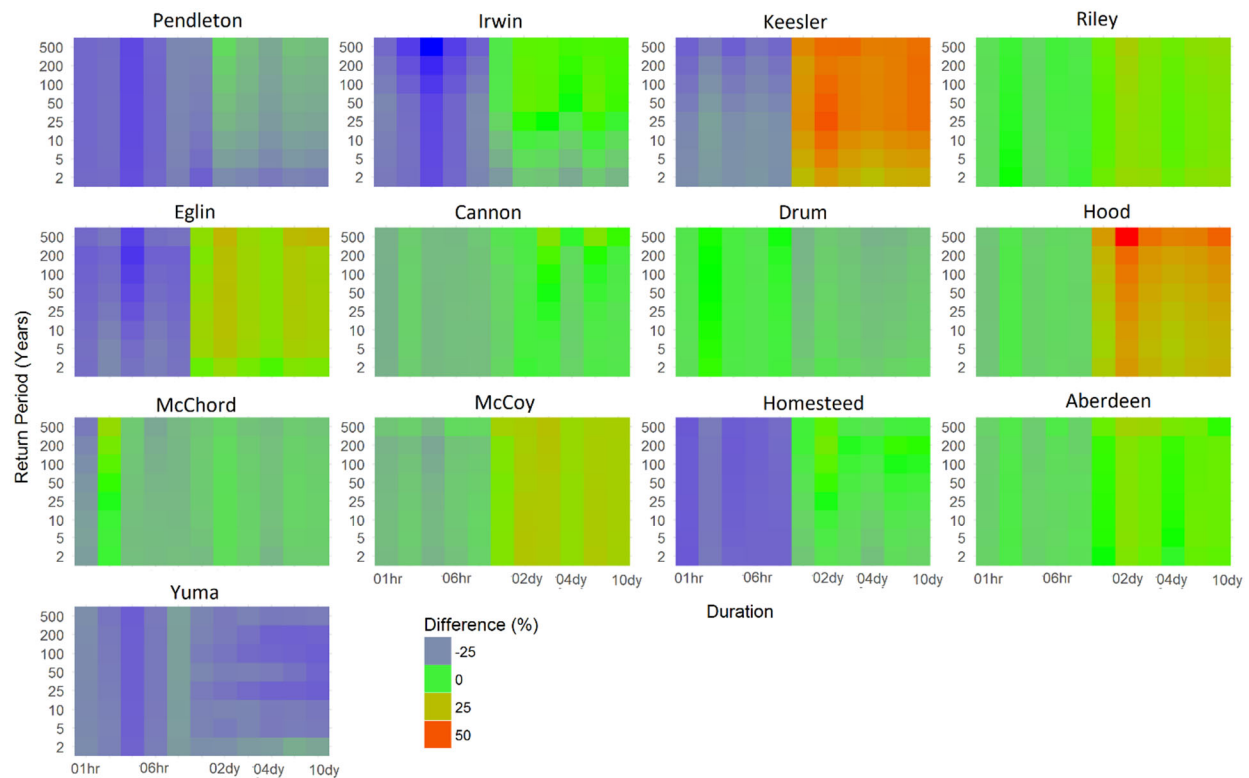


Figure 26. Comparison of the IDF curves with and without consideration of the future precipitation projections (CCSM, RCP 8.5)

The return periods from stationary (Equation 3) and nonstationary (Equations 4 and 5) can be directly compared to assess the impact of non-stationarity on IDF curves and associated engineering design and flooding risk. The impacts of the future precipitation and the associated non-stationarity vary from installation to installation. Figure 27 compares the return periods for one-day annual maximum precipitation with the stationary return periods estimated using only the past precipitation while the nonstationary return periods considered the past and future precipitation (CCSM and RCP 8.5). The future precipitation has relatively minor impacts on one-day return periods of annual maximum precipitation at Ft. McChord, Fort. Cannon, Ft. Kessler, Aberdeen and Homestead. The return periods increased for Camp Pendleton, Ft. Irwin, Yuma PG, but decreased for Ft. Hood, Eglin AFB, Ft. Riley, Ft. McCoy, Ft. Drum when the future precipitation was considered. For example, at Camp Pendleton, the one-day annual maximum precipitation with 75-year return period can have about 140-year return period in the future, leading to reduced risk of flooding under future climate condition. On the other hand, at Ft. McCoy and Eglin AFB, the 75-year storm become a 60-year storm when the future projection is considered, causing an increase in flooding risk. The impacts of nonstationarity are larger for infrastructures designed to handle storms with higher return periods. As a consequence, if a project in Ft. McCoy or Eglin AFB is to have, for example, a 100-year level of protection under

nonstationary conditions over the life of the facility, the initial design may have to be much larger. The opposite is true for large projects in Camp Pendleton and Yuma Proving Ground.

The risk of failure under nonstationary conditions was also illustrated using Figure 28. The dashed-lines in the figure show the risk for the stationary condition, whereas the solid lines are the risk for the nonstationary conditions using Eq. (10). For any given value of project design life time the risk under nonstationary conditions is bigger than that for stationary conditions when the solid line is above the dashed lines (e.g., Ft. Riley and Ft. McCoy). The risk increase due to nonstationarity is larger for higher return periods or project designed to handle larger storms. For example, for Ft. Riley, the 50-yr structures (blue lines) have 62% and 75% risk of failure (or 21% increase) during the 50-yr project life for stationary and nonstationary conditions, respectively. Consequently, if the risk of failure is to be maintained as in the stationary case, the infrastructures may have to be designed for a much higher return period or initial level of protection under nonstationarity.

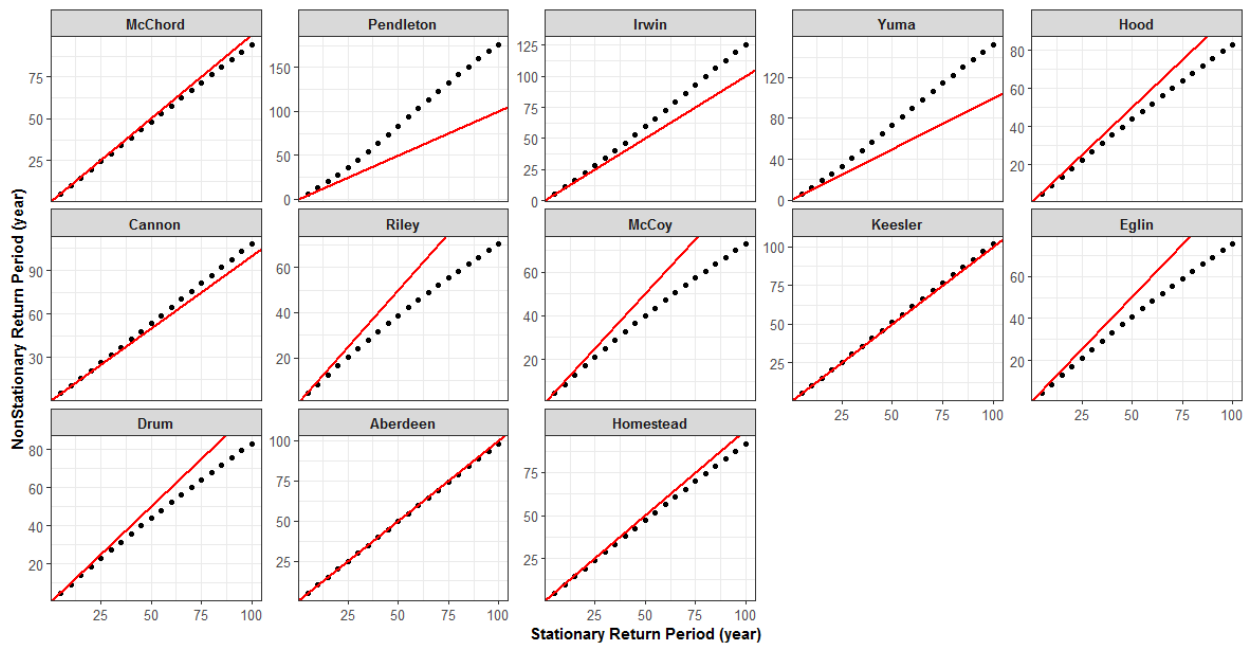


Figure 27. Comparison of return periods for one-day annual maximum precipitation under stationary and nonstationary conditions. The red-lines are 45° degree lines representing similar return periods. When the dots are higher than the red-lines, they indicate increase in return periods (or decrease frequencies) due to the non-stationarity of the storms

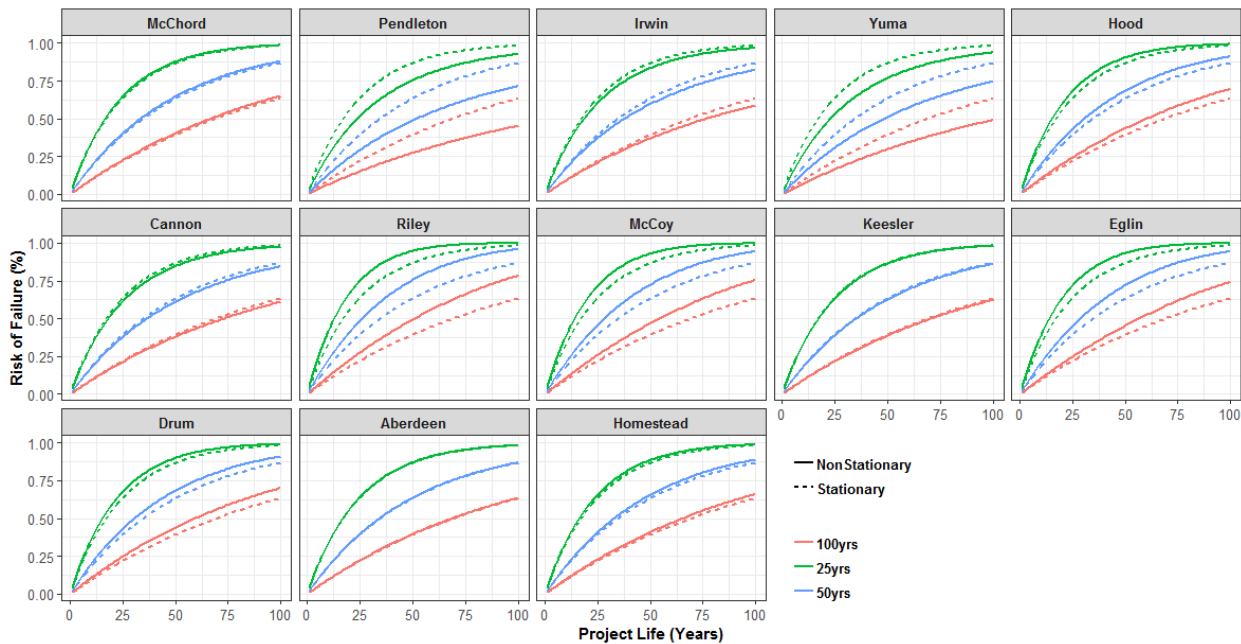


Figure 28. Risk of infrastructure failure as a function of project life under stationary (solid lines) and nonstationary (dash lines) storm conditions. The higher solid lines compared to the dash-lines indicate increased risk due to storm non-stationarity (e.g. Ft. Hood, Ft. McCoy, and Ft. Riley) and vice versa.

6.9. Runoff IDF Curves and Dominant Flood Causing Mechanisms

We have conducted a variety of data analyses from both rainfall, runoff, and watershed perspectives in order to better understand the flood behaviors and the potential use of the rainfall IDF curves for flood frequency analysis at each installation. We first explored the seasonality of storms and floods for all the installation since the dominant flood-generating processes at a given location can be strongly linked to the time of the year that major floods occur. The underlying processes that control floods were evaluated from (1) rainfall perspective using two hypotheses relating storm events and the resulted floods based on Berghuijs et al (2016), (2) runoff perspective using the shape of hydrographs associated with annual maximum peak flow based on Bhaskar et al (2000), and (3) watershed perspective using the combined role of watershed land coverage, soil types and topography based on a methodology used by the National Weather Service (Smith, 2003).

6.9.1. Storm and Flood Seasons

Analysis of the timing of annual maximum storm and annual peak flow events, based on representative rainfall and stream flow data from 1977 to 2017 for the 13 military installations, reveals some seasonality differences between the two events, highlighting the additional roles of other factors such as soil moisture conditions and snowmelt in causing the flooding events. The spider web Figure 29 shows the monthly occurrence of 1, 6, 12 and 24 hours annual maximum precipitations compared to the monthly occurrences of annual maximum peak flow and volume for some of the installations. For example, for the Lewis-McChord area, approximately 60% of

the maximum storms happened during November to January, while all the maximum peak flows occurred during December to March, with about 30% occurred in January. Despite 20% of the storms occurred in November, an annual maximum peak flow was not recorded during November. This can be because of the relatively dry soil moisture condition. On the other hand, even though there were not many storms during February and March, 20% and 15% of the annual maximum peak flows, respectively, occurred during these months. These may be explained by the saturated condition of the soil which can lead to major flood from relatively modest storm and the contribution of snowmelt. For Camp Pendleton, there is relatively a good match or overlap between the storm months and the peak flow months, which mostly happen during January. Given the region is arid, soil saturation is expected to be rare and thus the observed maximum peak flows are most likely a direct response to the maximum storm as in the case of flash floods. The maximum peak flows occurred throughout the year in Aberdeen PG without showing any apparent relationship with the maximum storms which mostly occurred during the summer months. The Fort McCoy area has three flood seasons or separate months which are not directly related with the summer maximum storm season. The flooding seasons in March and June are most likely related to snowmelt since only a few maximum storms happen during those months.

Similar observations can be made for the rest of the installations. But one consistent finding for most of the installations (except Camp Pendleton) is that the flood events are poorly explained by rainfall characteristics alone, making direct usage of the rainfall IDF curves to estimate the flood frequency and design stormwater drainages difficult and unreliable. Identifying the relevant physical processes and variables that control flood also help in selecting the appropriate hydrologic models.

A close look at the daily annual maximum precipitation and peak flow seasons in Figure 29 also confirms the difference between the seasons. In the Ft. Drum area, the annual daily maximum rainfall happened over extended period, while the peak runoff occurred over a limited period. Such difference in storm and flood seasons may lead to overestimation of the flooding risk using the IDF curves directly since most of the annual maximum storms do not necessarily cause annual peak flow. Figure 30 illustrates the impacts of the seasons difference on IDF curves. Instead of picking annual maximum precipitation values independent of the flood season, in this case, the annual maximum precipitation values were drawn only during the entire flood period (left side panel of Figure 31) and during the 25%-50% quantiles flood period (right side panel of Figure 31). Overall, the impacts are significant for smaller return periods, but as the return period and duration increased the difference become smaller and the IDF value can serve as a good indicator of flooding risk. This is consistent to the expectation that major storms (or storms with larger return periods and longer durations) most likely lead to the annual maximum peak flow.

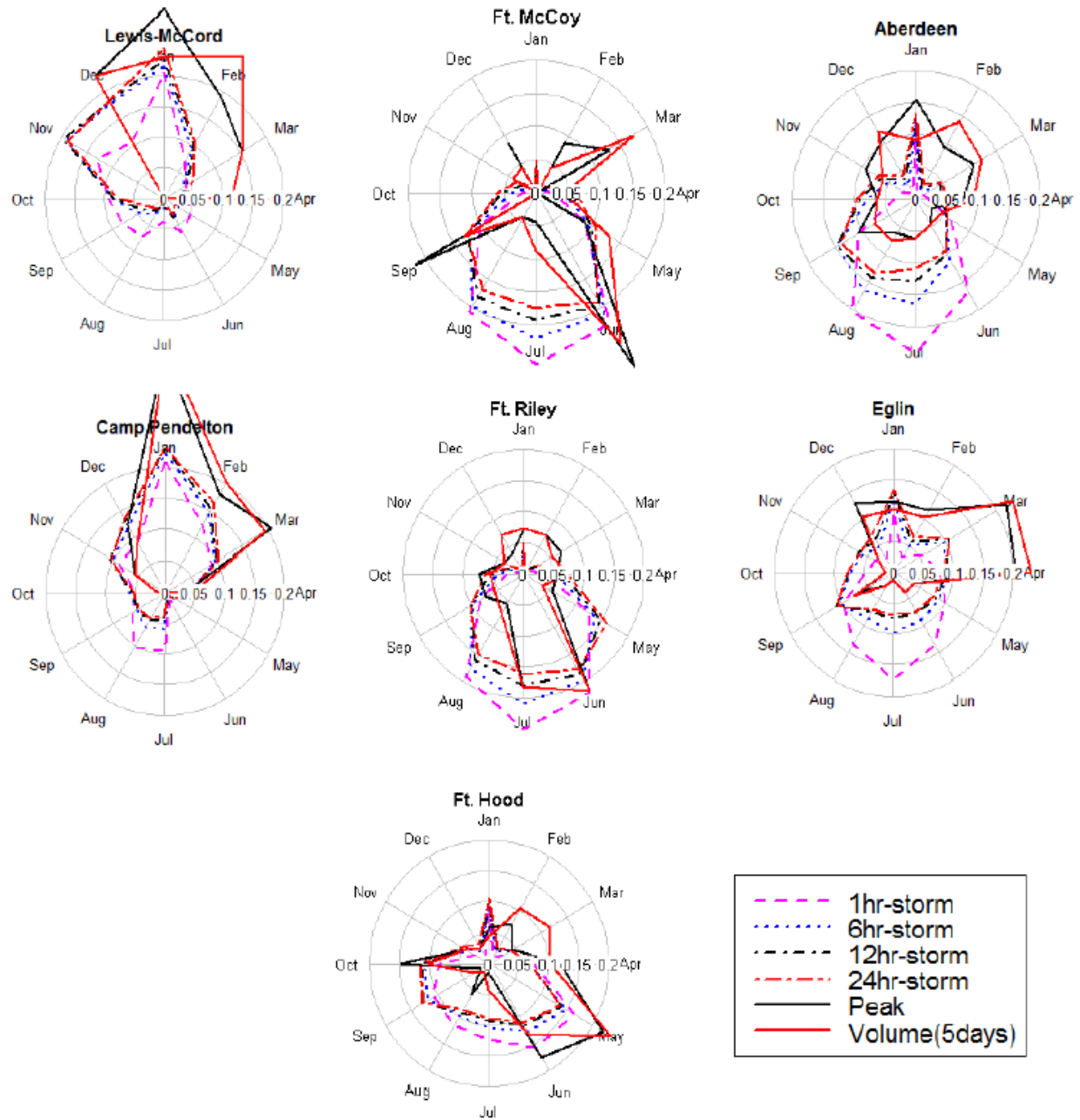


Figure 29. Seasonality of storms, peak flow and volume. The concentric circles are percentages of occurrence of storm, peak flow and volume within a specific month over the past 40 years (1977-2017).

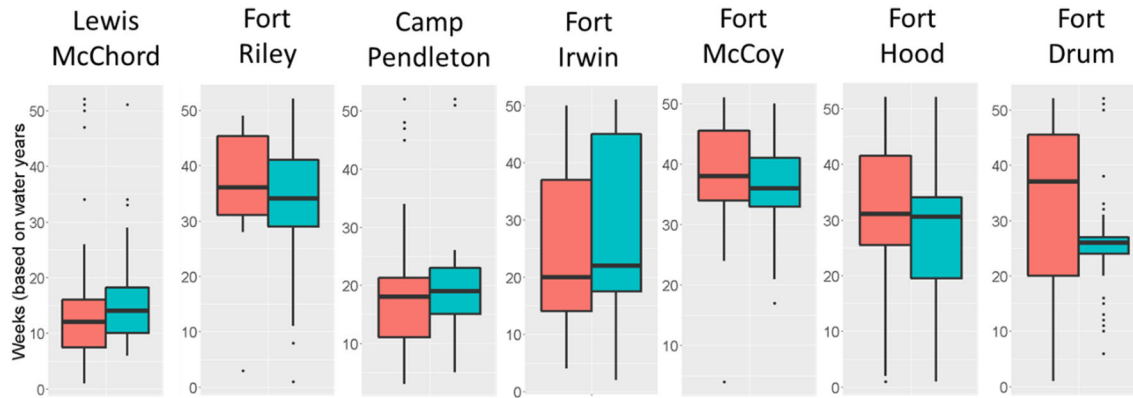


Figure 30. The season difference between one-day annual maximum precipitation (orange boxplots) and annual peak flow (green boxplots).

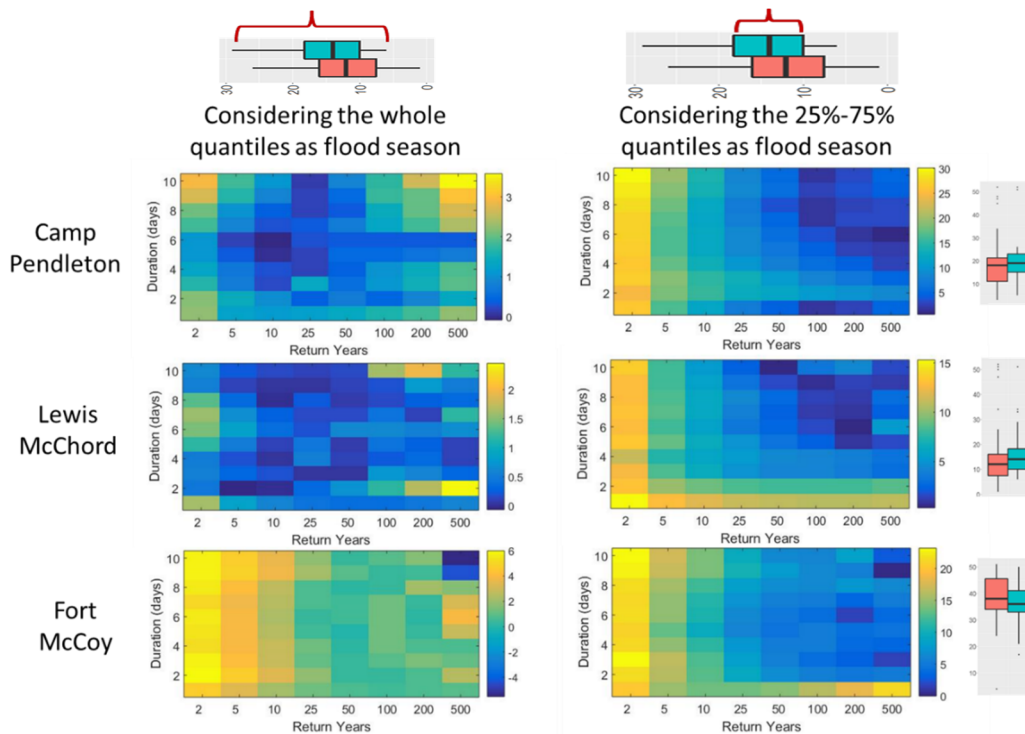


Figure 31. Impacts of the seasons difference between annual maximum precipitation and annual peak flood on IDF values for ranges of durations and return periods. The IDF values in the left and right panels were computed using annual maximum rainfall values drawn from the entire flood season and from the 25%-75% quantile flood season, respectively.

6.9.2. Flood Causing Mechanism: Rainfall Perspective

The direct effects of rainfall on food events were tested using two hypotheses similar to those used by Berghuijs et al (2016). The first hypothesis is that flooding is caused by a single largest precipitation event, while the second hypothesis is that flooding is caused by a series of

precipitation events. In order to test these two hypotheses, we have used a combined daily precipitation data obtained from stations near to the installation and daily streamflow data from a representative USGS stream gauges (i.e., gauges located closed to the installations and on major river or creek passing through or adjacent to the installations). The daily streamflow and precipitation cover from 1977 to 2017 for all the stations. To test the first hypothesis, first we determined the dates associated with the annual maximum peak flow and checked whether the annual maximum precipitation in any given year happened within 10 days prior to the dates of the annual maximum peak flows. The selection of 10 days was based on our prior analysis of the flood lag-time in the watersheds associated with the military installations. As shown in Figure 32, more than 60% of the annual maximum peak flows occurred within 10 days after the annual maximum precipitations in the Camp Pendleton over the past 40 years (1977-2017). This suggests that the annual flooding in the Camp Pendleton mostly resulted from single largest annual precipitation event. Other installations, where the annual flooding is mostly related to single major storm event include Eglin AFB (50%), Keesler AFB (44%), Lewis-McChord (43%) and Ft McCoy (42%). In those areas, where there is a considerable correspondence between the storm and flood events, the result from rainfall IDF curves can be readily applied to estimate the magnitude and frequency of peak flows.

To test the second hypothesis, we aggregated the 10-day precipitations prior to the annual maximum peak flow and compared them to the annual maximum 10-day precipitations. Compared to the single major storm, the largest precipitation events over 10-days did not cause the majority of the annual maximum peak flows. The largest percentage is for Ft Riley (20%), which means only 20% over the past 40 years that the annual maximum 10 days precipitation events caused the annual maximum peak flow.

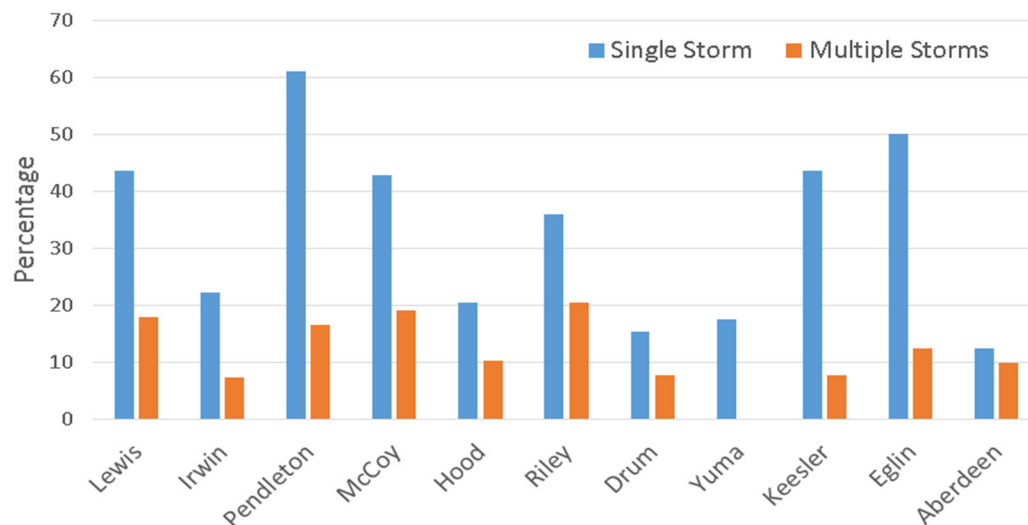


Figure 32. Percentage of direct link between single storm and multiple storm events with flooding events

6.9.3. Flood Causing Mechanism: Runoff Perspective

The flooding events (annual maximum peak flows) at each installation were examined from a runoff perspective using a methodology developed by Bhaskar et al (2000). In the past, floods were commonly characterized by rainfall and limited effort was made to examine them directly from a runoff perspective. Using daily streamflow data from the USGS gauges located close to the military installations, we have generated the runoff hydrographs associated with the annual maximum peak flow. In order to have a consistent analysis among the installations, the streamflow measurements from 1977 to 2017 were used for all the installations, providing 40 runoff hydrographs corresponding to the annual maximum peak runoffs (Figure 33). The methodology uses the runoff hydrograph characteristics such as the rate of the rising limb, time to peak and magnitude of the peak to determine flash flood index. The average of the 40 hydrographs (shown as solid lines in Figure 33) was used for the analysis.

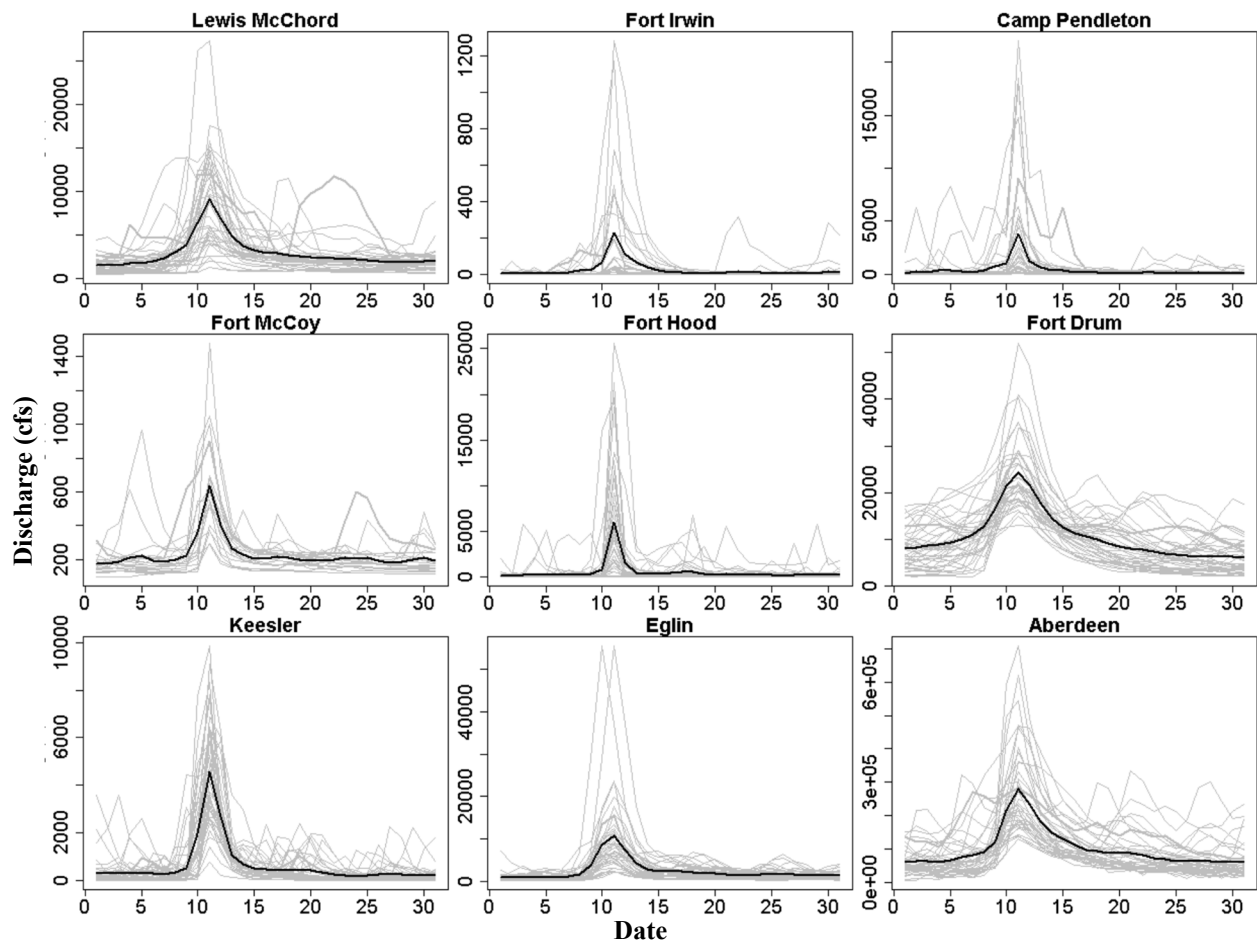


Figure 33. The hydrographs corresponding to the annual maximum peak flows at the different military installations.

The flash flood index (RF in Table 2) was calculated based on the rising rate of the hydrograph (RK), the magnitude of the peak flow (RM) compared to long-term average flow and the flood response time or the time the flood takes to reach the peak (RT). The rising section of the hydrograph was assumed to be exponential, and computed using $Q_t = Q_o e^{Kt}$ where Q_o is the initial discharge before the flood events start, Q_t is the discharge close to the time to peak (TP), t is time in days and K is the rising curve gradient (day^{-1}). Using the Q_p , Q_o and TP provided in the table below, we first calculated the K values which were then converted to relative severity factors of K (RK) based on a tabular relationship provided by Bhaskar et al (2000). In the tabular relationship, the K value ranges from 0 to 35, while the RK values ranges from 1 to 7, with 1 being relatively flat hydrograph. Similarly, to determine the relative severity factors for the magnitude of peak flow (RM), first the flood magnitude ratio, M , was computed using $M = QP / Q_{avg}$, which is the ratio peak flow over long-term average flow. The ratio was then converted to RM using another tabular relationship from Bhaskar et al (2000). The RM can range from 1 to 16, with 1 being the peak flow to be relatively close to the long-term average flow. The relative severity factor for the flood response time (RT) was computed using directly the time to peak (TP) and its tabular relationship with RT. The RT can range from 1 to 10, with 1 being the flood response time is more than a day. Since we have used daily datasets, the presented flash flood index values in Table 2 were not sufficiently resolved to characterize flood behaviors at sub-daily time step. We currently in the process of adopting the approach for the hourly dataset. Finally, the flash flood index (RF), shown in the last column of Table 2, was computed by adding the three relative severity factors. The RF value can range from 3 to 33, with higher values indicating the likelihood of the annual maximum peak flow was caused by the flash flood.

Table 2. Flash flood index based on runoff hydrographs for the 13 military installations

Stations	Rainfall Characteristics		Flood Runoff Characteristics						Flood Indexing Parameters						
	Rainfall volume (mm)	Rainfall Duration (day)	Flood Peak (cfs)	Time Base (day)	Time to Peak, TP (day)	Lag Time (day)	Average flow (cfs)	Initial Flow, (cfs)	Rising curve gradient, K	Flood Mangintude Ratio, M	Flood response time, TP(hr)	Relative Severity Factors			Flash Flood Index, RF
												RK	RM	RT	
Lewis	74.3	1.03	9024.1	9.59	3.64	2.08	1254.3	4143.36	0.6	7.2	87.4	1	1	1	3
Irwin	15.4	2.04	224.6	6.41	2.85	2.19	3.6	140.39	1.3	62.6	68.4	1	16	1	18
Pendleton	61.3	2.06	3774.5	6.44	2.94	1.53	66.3	1311.38	1.3	56.9	70.7	1	16	1	18
McCoy	52.9	1.7	638.2	7.8	3.45	1.35	161.5	367.6	0.4	4.0	82.8	1	1	1	3
Hood	46.3	1.49	5978.1	4.72	1.92	1.74	102	4107.92	1.4	58.6	46.2	1	13	1	15
Riley	54.3	1.82	17396.2	11.08	4.51	2.41	2464.1	10711.62	0.5	7.1	108.3	1	2	1	4
Drum	28.0	1.67	24210.3	11.85	6.33	3.82	4656.9	11918.9	0.3	5.2	152.0	1	1	1	3
Yuma	9.3	1.38	1675.2	7.62	3.8	4.35	394	1303.19	1.2	4.3	91.2	1	3	1	5
Keesler	141.0	1.9	4599.7	7.13	3.15	0.77	202.7	1781.33	1.0	22.7	75.7	3	3	1	7
Eglin	135.1	1.9	11352.2	8.03	3.15	1.65	1102.1	4021.9	0.7	10.3	75.6	1	3	1	5
Aberdeen	47.7	1.92	279900	10.4	4.62	3.3	40145.7	131027.5	0.5	7.0	111.0	1	1	1	3

6.9.4. Flood Causing Mechanism: Watershed Perspective

We have adopted the flash flood index (Smith 2003), which is commonly used by the National Weather Service (NWS) to predict occurrences of flash floods, to qualitatively assess the flash flood risk in the watershed associated to the military installation. The index was calculated by overlaying the land cover, slope and soil type/texture maps in the watershed. An index value of 1

indicates a minimum flash flood risk, while an index of 10 indicates a maximum flash flood risk within the watershed. In general, areas with a higher slope, clay soil type, and sparse vegetation coverage are expected to have a higher potential for flash floods. As shown in Figure 34, the Lewis-McChord installation is located in the watershed section where there is less potential for flash floods caused by watershed characteristics, while on the other hand has the Camp Pendleton is located in area where there is considerable potential for the flash flood from the watershed perspective (Figure 34). Noted that this risk is solely from the watershed perspective and does not consider the soil moisture conditions, snowmelt effect and storm characteristics. We have also examined the 100-year return period flood maps obtained from Federal Emergency Management Agency (FEMA) to gain insight on the installation's vulnerability to the floods. Despite the major historical floods recorded in the Camp Pendleton, the FEMA's 100-year flood events were not identified in and around the installation. This makes the results from this project to be useful in better characterizing the flood vulnerability and adopting an appropriate stormwater management system.

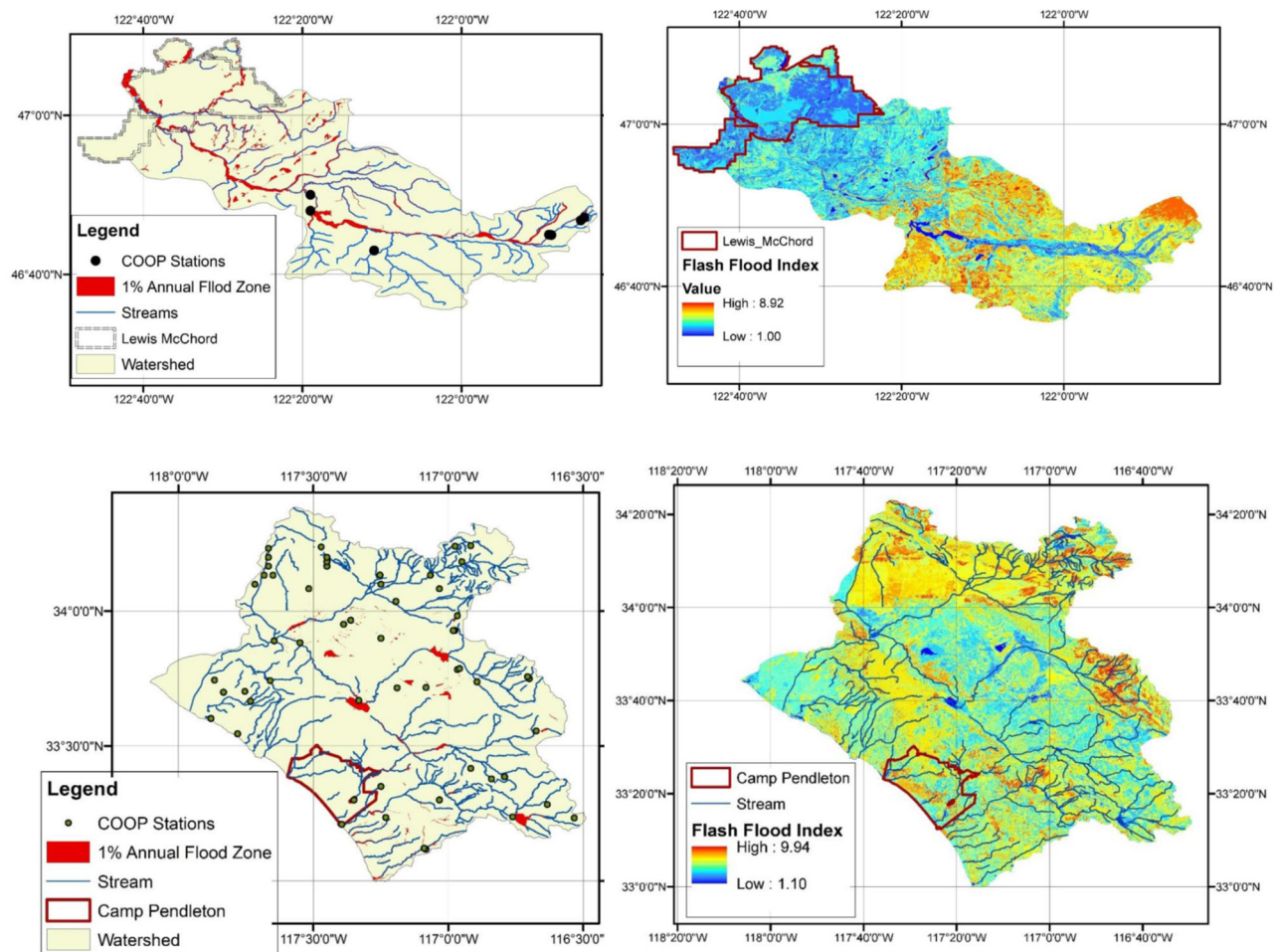


Figure 34. The 100-year FEMA flood maps (left) and flash flood index maps (right) for a watershed associated with Lewis-McChord and Camp Pendleton

6.10. Hydrologic Modeling for Flood Frequency Analysis

A preliminary modeling effort was made to develop a hydrologic model balancing the event-based simulation to utilize the rainfall information from IDF curves and continuous simulation to better represent the antecedent soil moisture content. The HEC-HMS model with Soil Moisture Accounting (SMA) approach provide the desired interface between event-based and continuous simulations. As discussed in the previous sections, direct translation of design storms obtained from the rainfall IDF curves to estimate peak runoff and volume is difficult because of the different flood causing mechanisms and effects of the soil moisture and snow conditions. For example, from our analysis which is also illustrated in Figure 35, we noticed that a large storm events during summer may result in relatively small peak flow and runoff volume in the Lewis-McChord region, while a relative mild storms not characterized by the IDF curves can result to major flooding event if those storms occurred during a winter season when the soil moisture is near saturation.

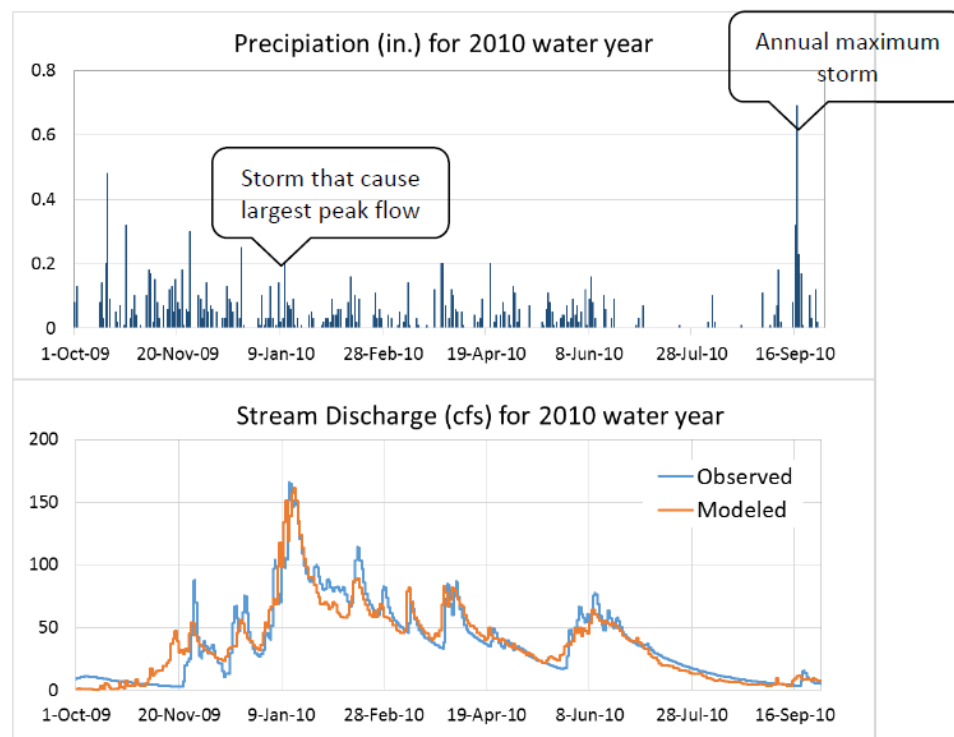


Figure 35. Precipitation time series in the Clover Creek watershed in 2010 (top) and the associated discharge at the outlet of the watershed (bottom). The annual maximum storm, which occurred in September did not generate a significant flood events, while the storms in early January generated the maximum peak flow. These responses of the watershed might be attributed to the soil moisture condition before the storms.

The HEC-HMS model was developed for the Clover Creek watershed (Figure 36), which contains a large portion of the McChord AFB near Seattle, to simulate the daily annual flow at the watershed outlet. The model was developed and calibrated based on rainfall and discharge data

from 1996 during which the watershed experienced a historical. Developing the model to simulate flow conditions for the entire year, instead of the flow condition in response to a specific storm event, allows to properly account for the soil moisture condition. The model was then validate based on a typical flood year 2010, which was also used to simulate the design storms obtained from the rainfall IDF curves and generate the runoff IDF curves. The calibration and validation results are provided in Figure 37, demonstrating the model ability to represent the rainfall/runoff process adequately. The validated model and the 2010 rainfall condition that caused the annual maximum peak flow was then replaced by the design storms obtained from the IDF curves to develop the runoff IDF curves shown in Figure 38. The runoff IDF curves show that the return period for the 1996 flood was over 100 years, while the 2014 annual maximum peak flow has about 5 years return period. The relative leveling of the IDF curves after 60hr indicates the time of concentration of the watershed is around 60hr. These results will be further validated by comparing them with the results obtained from the frequency analysis of the observed discharged.

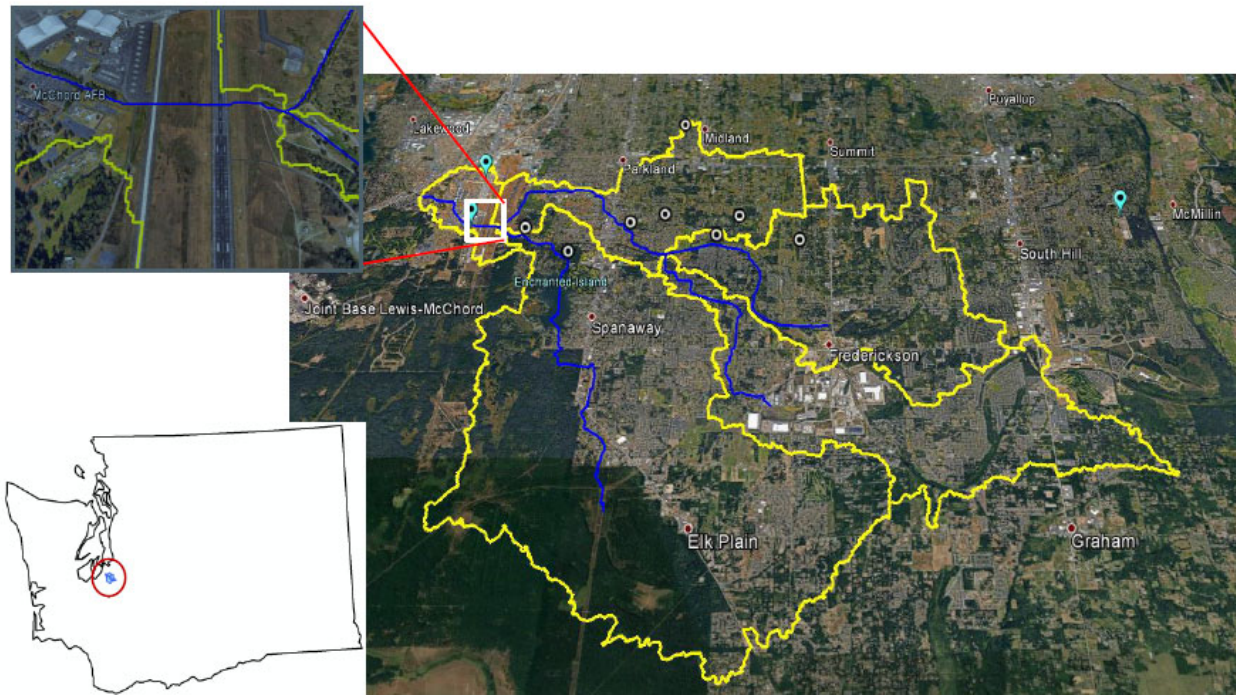


Figure 36. Location map for the Clover Creek and the McChord AFB south of Seattle. The Creek pass underneath the runway using culverts.

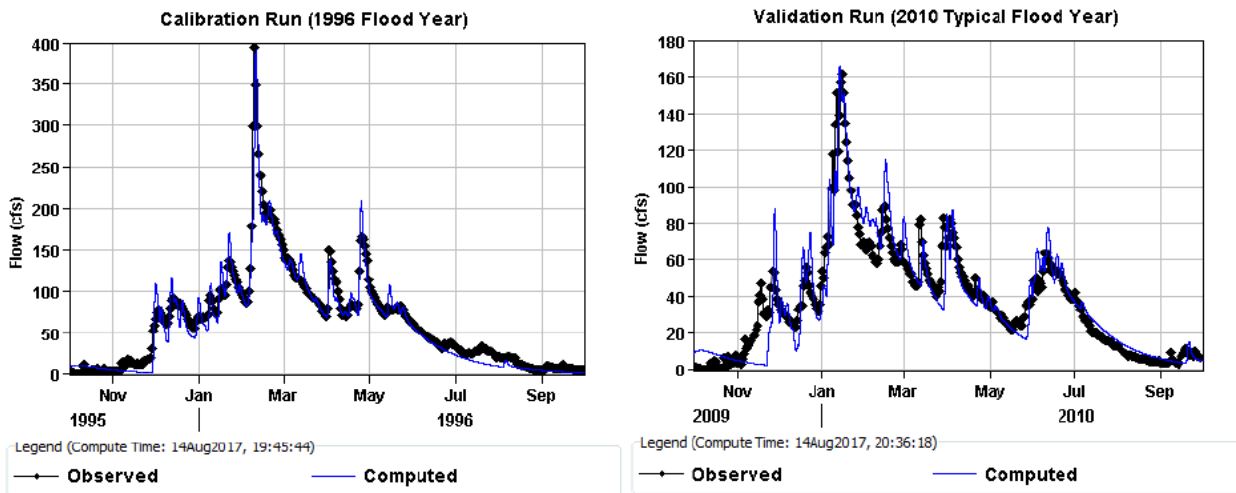


Figure 37. HEC-HMS calibration and validation results for the annual simulations compared to the observed discharge.

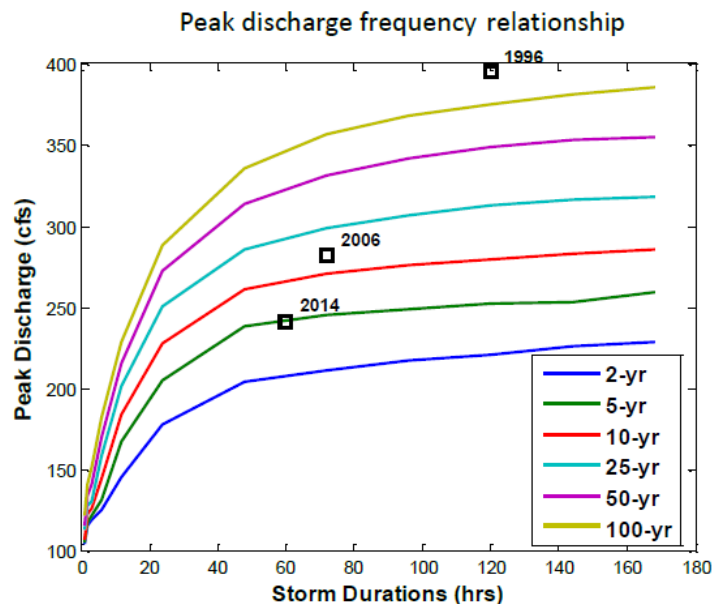


Figure 38. The runoff IDF curves for the Clover Creek watershed at its outlet, which is located near to the runway in McChord AFB.

6.11. Snowmelt Modeling and Incorporation to the Rainfall IDF Curves

We have performed snowmelt modeling using the UEB tool for four out of 13 military bases that are likely affected by the snow accumulation and melt. Those sites are Aberdeen PG (APG), Ft. Drum (FD), Ft. McCoy (FM), and Lewis McChord (LM). The hourly snowmelt projections from the UEB model was combined with precipitation to form the time series of the total amount

of water, namely rainfall + snowmelt time series. The annual maximum series can be extracted from rainfall + snowmelt data for each station.

The annual maximum series provide a base for developing IDFs. Figure 39 shows changes in annual maximum series between precipitations without considering snowmelt and rainfall + snowmelt for Fort Drum as an example. The statistics about mean, low and upper quantiles, minimum and maximum, and some outliers for the site were based on precipitation data and snowmelt model output for all available locations. Although there are some variation, in general, the mean and the range between first and third quantiles are greater for rainfall + snowmelt annual maximums than those of precipitation.

In order to further identify the causes of the difference in annual maximum series, we evaluate changes in annual maximums from precipitation to rainfall + snowmelt each year for most of locations. We found basically two scenarios as shown in Figure 40. In scenario 1, the precipitation records from NOAA often represent snowfall or both snowfall and rainfall as temperature is near or below zero Celsius. The UEB snowmelt model will determine what amount of precipitation is considered as snow based on temperature at hourly step. As an example, in 1971 at station USC00304912, the annual maximum of 68 mm precipitation was actually contributing as snow to the snowpack (SWE). The maximum liquid (rainfall plus snowmelt) of that year was 32 mm in August. The scenario 1 suggests a decrease in annual maximum from 68 mm to 32 mm for 1971 (Figure 40a). In scenario 2, an increase in liquid water (rainfall plus snowmelt) is observed for annual maximums. For example, in 1978, a rainfall and snowmelt event were occurred due to warm weather in March. The liquid water (rainfall + snowmelt) is 95 mm, which is much higher than annual maximum precipitation record of 55 mm as rain in September. Scenario 2 represent a case for increased annual maximums. For most of locations, scenario 2 occurs more often than scenario 1 as indicated by statistical measures at Ft. Drum (Figure 39). However, at Lewis McChord, changes in AMS are more associated with scenario 1 than scenario 2, resulting in decrease in AMS.

Changes in AMS based on output from the UEB snowmelt modeling will significantly affect the IDF results. For most of scenario 2 cases, increased AMS (mean, quantile range, minimum and maximum, and outliers) will result in higher IDF values as shown in Figure 41. At Ft. Drum site, the average of rainfall + snowmelt for 1 day duration among 31 locations increases by 22% for 10-year event, 24% for 50-year event, and 25 % for 100-year event (Figure 41a, b, and c). For scenario 1 cases, IDF values are reduced due to decreased AMS predicted from the snowmelt model. Those cases occurred more at Lewis McChord site.

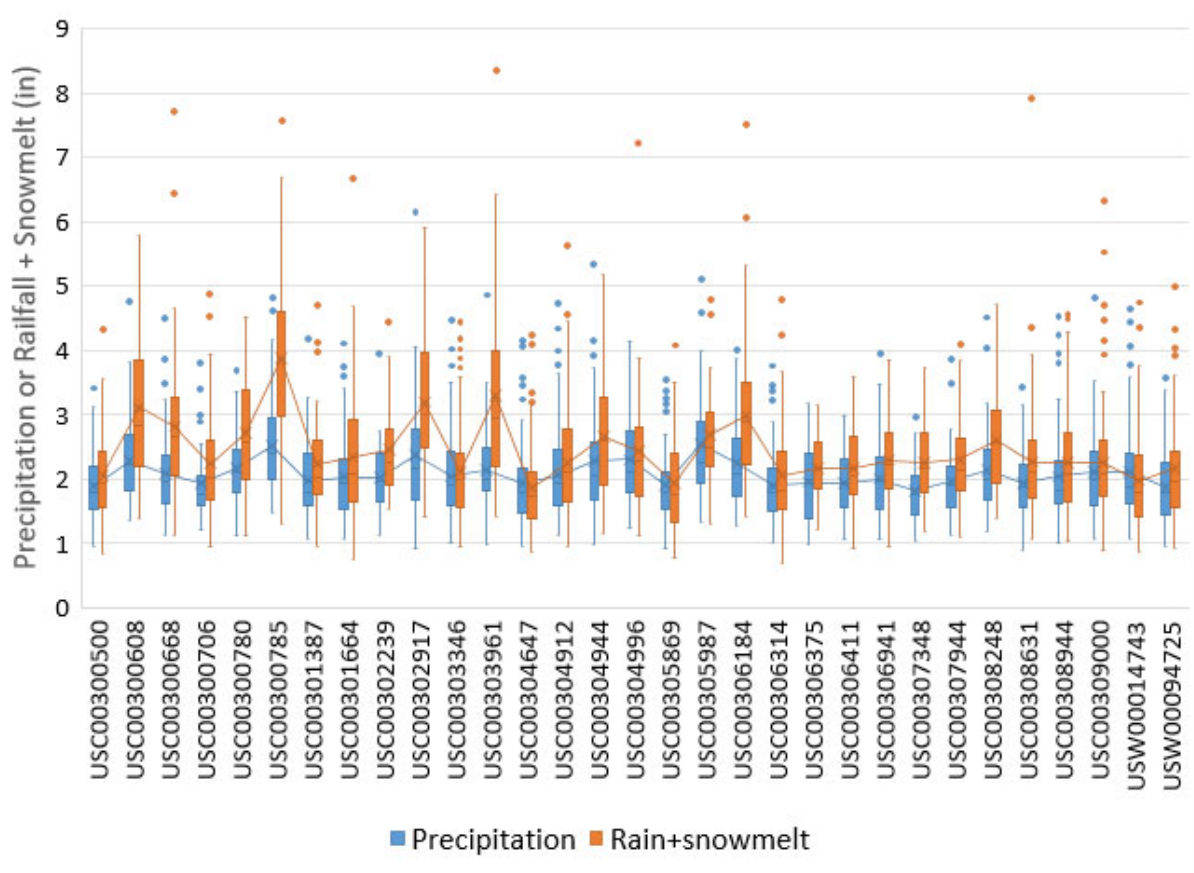


Figure 39. Comparison of annual maximum series determined based on precipitation records and rainfall plus snowmelt predicted by snowmelt modeling at all stations for Fort Drum site. The statistical measures include mean (marker for each station and line to link among stations), first and third quantiles as shown as the bottom and top of the box, minimum and maximum as shown by the vertical line, and dots that are identified as outliers (1.5 times of interquartile range).

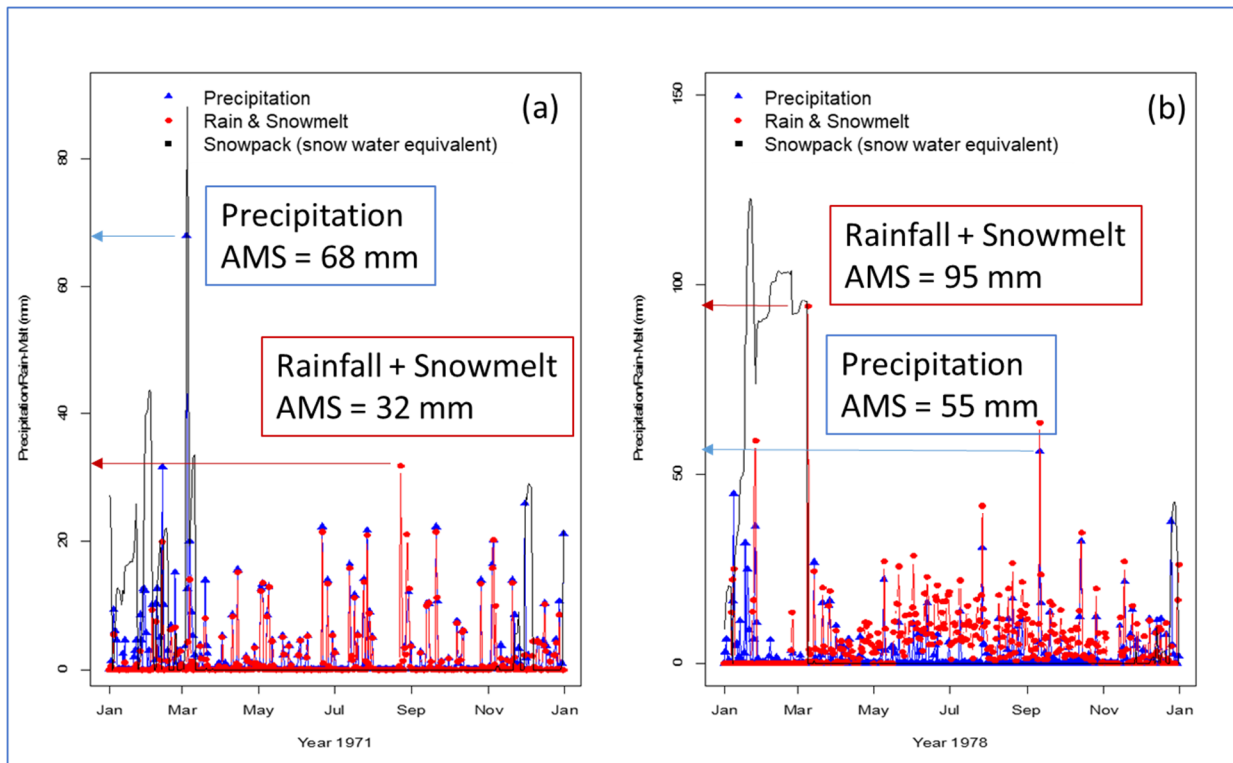
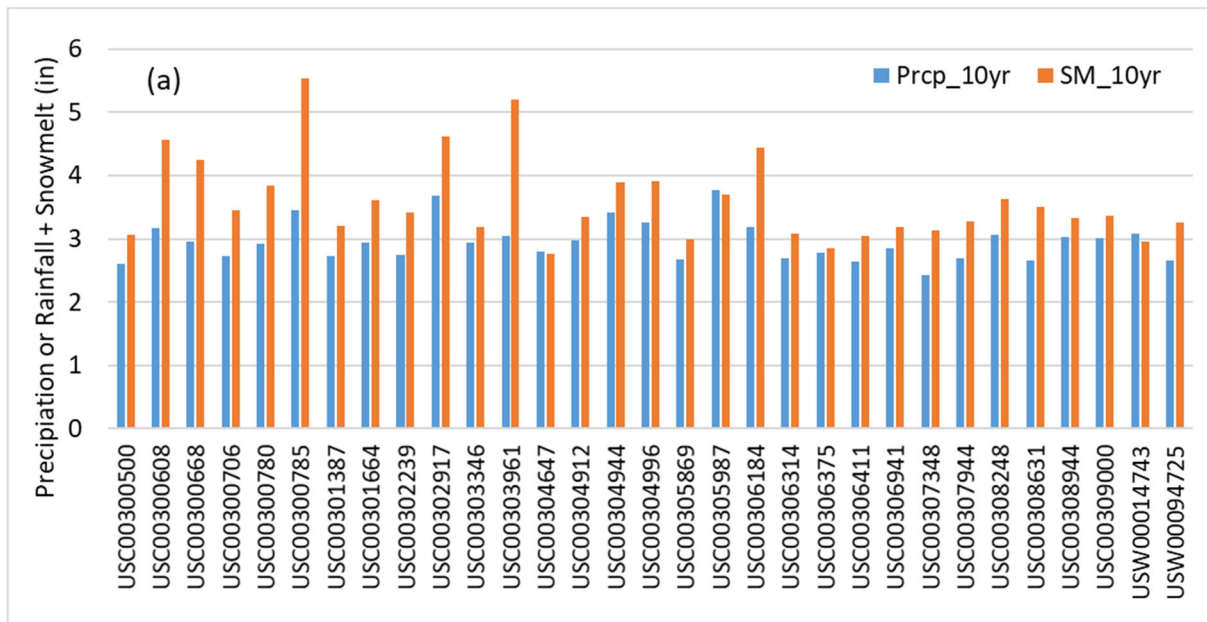


Figure 40. Effects of snow and snowmelt on annual maximum series determination (USC00304912). Scenario 1 (a): precipitation overestimates water available for runoff during frozen days. Scenario 2 (b): precipitation underestimates water available for runoff from rain and snowmelt in warm days with snowpack on ground.



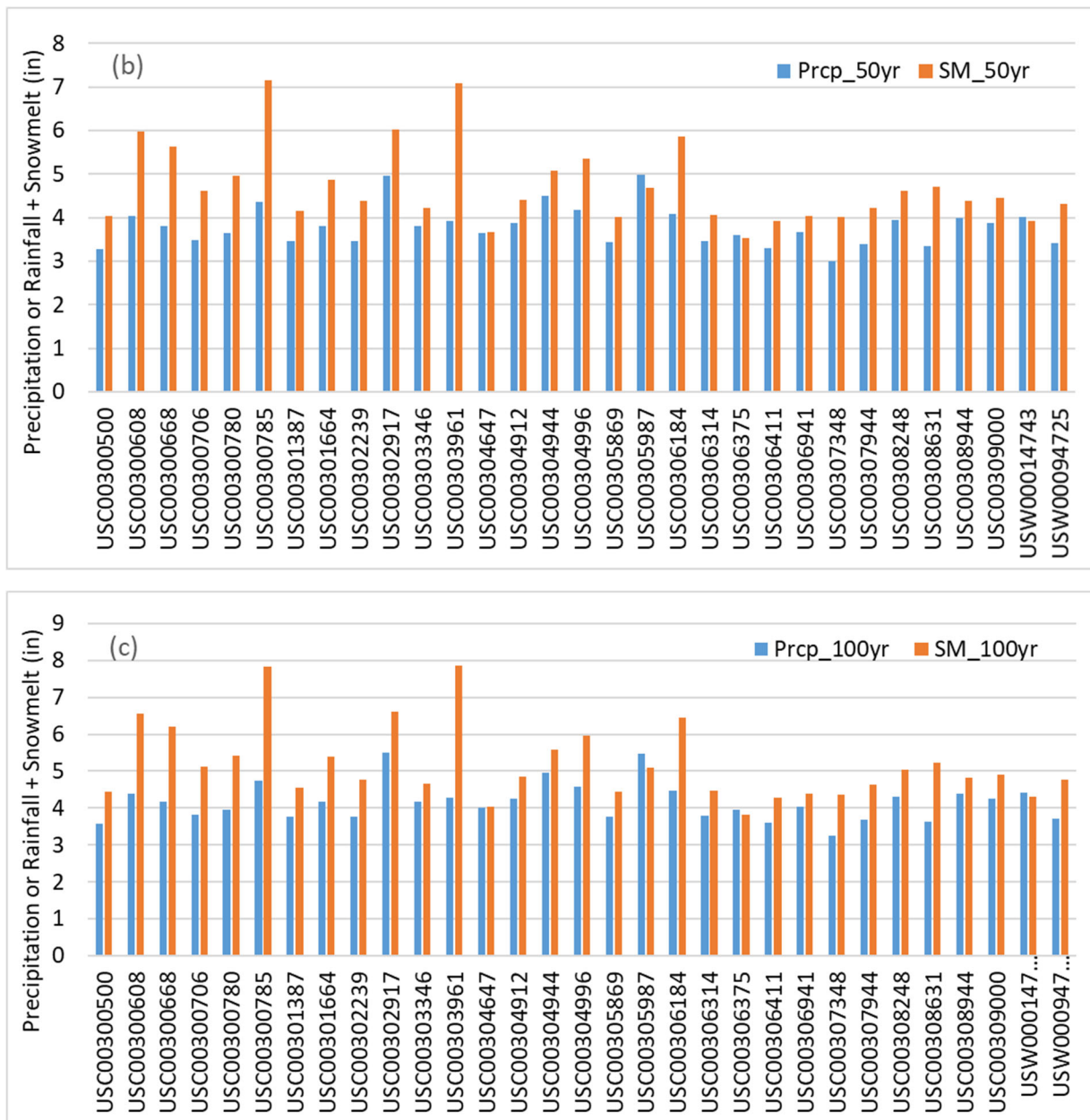


Figure 41. Comparison of IDF values between precipitation and rainfall + snowmelt for 31 locations at Fort Drum, specifically 1-day precipitation and rainfall + snowmelt for 10-year (a), 50-year (b) and 100-year (c) events.

6.12. Interactive Web-based GIS Interface

The project website (Figure 42) provides brief project summary; description of the web-based tool with a link to launch it; identification of the project team and sponsor; news section with announcements about project activities, help content for the tool, a link to request the underlying data, this report, and published manuscripts. After the web-based tool is launched, users select a category and dataset combination, and a site from the menus at the top of the map panel. The map is zoomed to the project location, and grid and station overlays are added for the chosen category

and dataset. Clicking a station or grid cell on the map highlights the location and populates the results panel with an IDF curve of the results. Other features within the map panel include interactive zooming and panning; turning overlays on and off; and changing the base map between street, shaded, topographic, and other options. Within the results panel the IDF axes can be changed; subsets of frequencies or durations can be turned on and off; and lowest, best, and highest estimates can be displayed. There is also a table view listing the values in tabular form, and an export button allows a spreadsheet of the values to be downloaded. The web-based tool interface is shown in Figure 43 with an example session showing the Fort Lewis - McChord Air Force Base location on the left panel with a station northeast of the site selected, and the right panel showing frequency IDF curves from 2 to 500 years by precipitation depth in mm and duration in hours and days.

Compared to traditional workstation databases and software, this hosting system with a web-based interface is more efficient to host, maintain, and update. It provides access to users through free software they usually already have, through an interface they can implement without significant training. To familiarize users with the tool, a webinar will be presented and a recording will be available on the project website. Other help content will include a brief training video with a description of the project, overview of the website, and instructions for the tool interface to facilitate understanding the project and how to use the web-based tool.

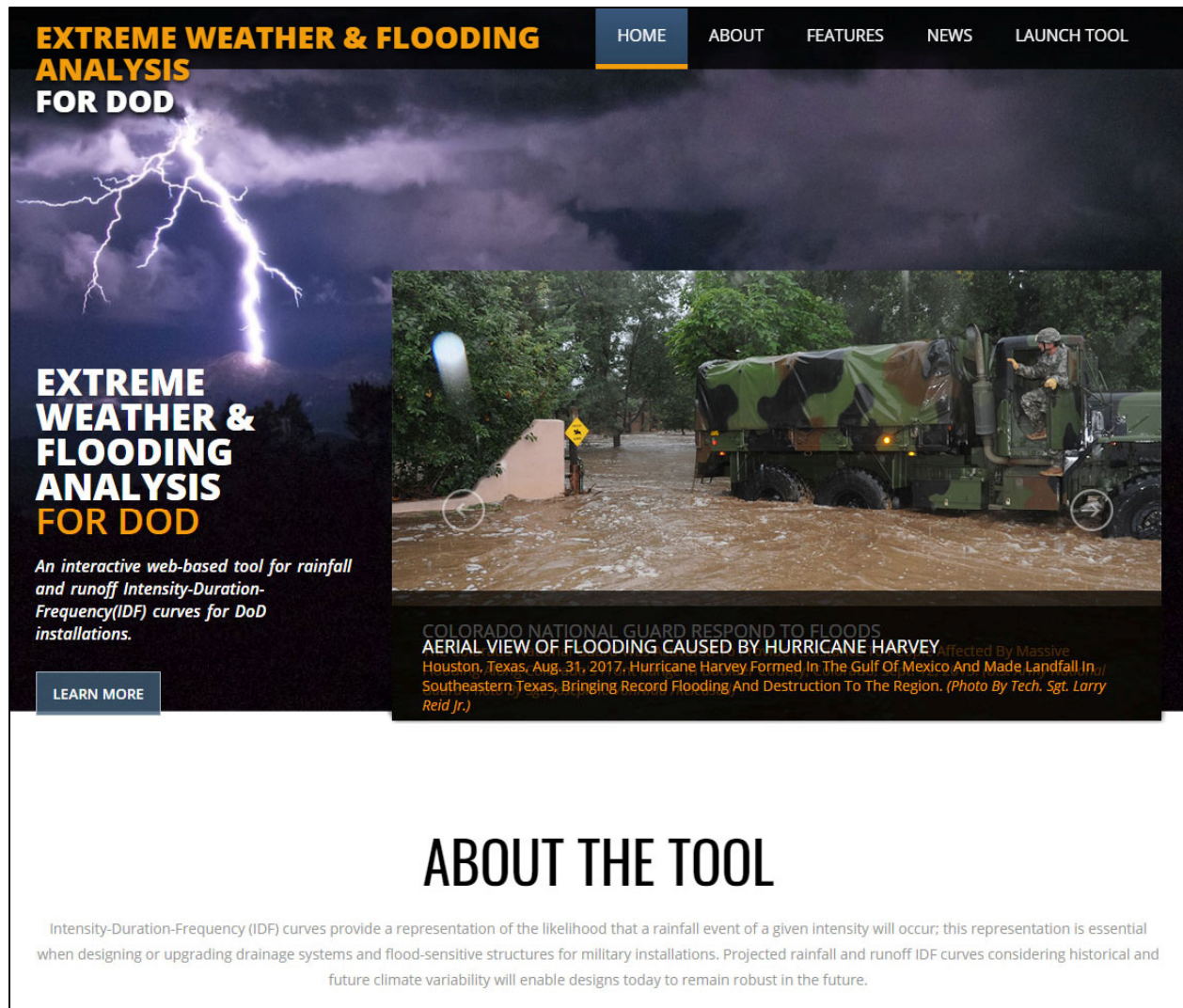


Figure 42. Project Website (<https://bogi.evs.anl.gov/dodewa/tool/index.html>).

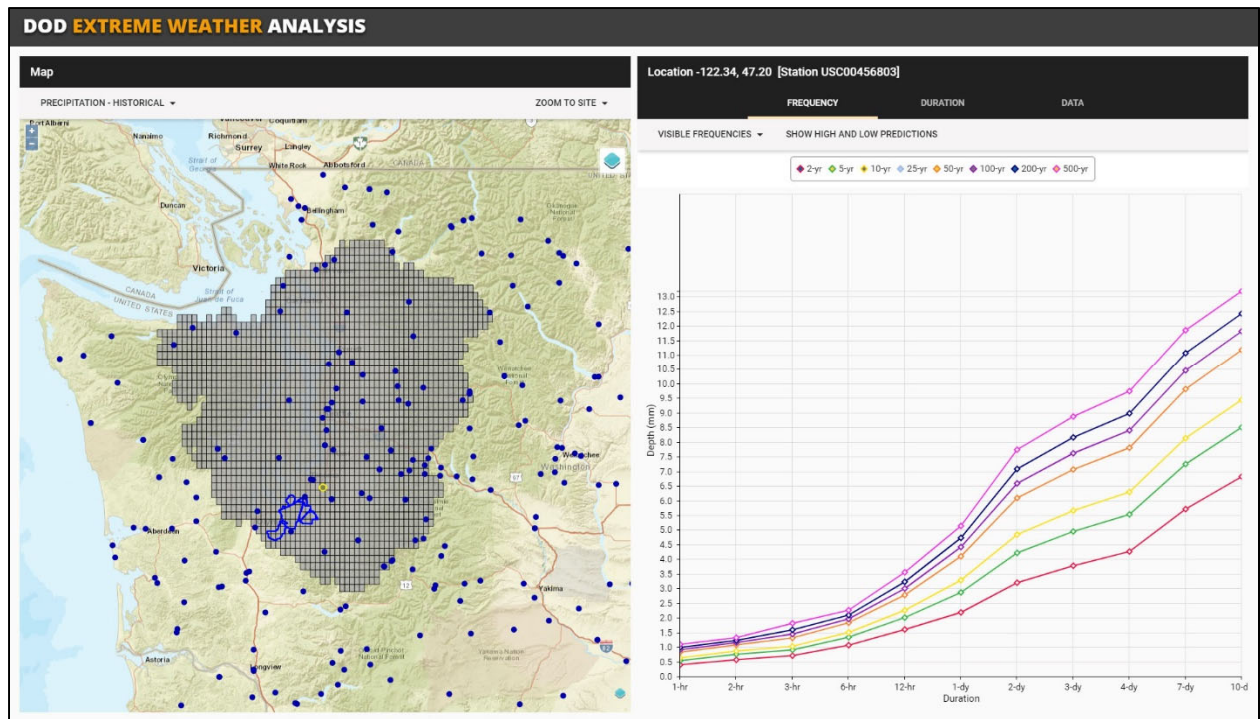


Figure 43. Web-based mapping tool, showing the Fort Lewis - McChord Air Force Base vicinity on the left panel with a station northeast of the site selected, and an IDF curve on the right panel.

7. CONCLUSION AND IMPLICATIONS FOR FUTURE RESEARCH/IMPLEMENTATION

Trends in Extreme Precipitations.

We have conducted trend analyses using all the stations near to our study installations and containing more than 30 years complete records, and using representative long-term precipitations data obtained by combining data from nearby stations. For all the installations and storm durations (1hr – 10day) we have considered, the historical records of annual maximum precipitations showed no spatially consistent significant trends at both station and regional levels. Approximately 10%-16% of stations showed statistically significant increasing trends, while only 4%-6% of stations showed decreasing trends in the past. None of the climatologically homogenous regions (e.g. Figure 16) showed significant trends. Relatively more stations in the Midwest (Ft. McCoy and Ft Riley) and Northeast (Ft. Drum and Aberdeen PG) showed increasing trends, particularly for daily and longer durations storms. However, when the future precipitations are considered, considerably more stations (> 50%) showed increasing trend in daily and longer durations storms while a decreasing trend in sub-daily storms magnitudes at the majority of installations. The differences are not clearly evident in the resulted trends from either the CCSM and GFDL climate models or the RCP 8.5 and 4.5 emission scenarios. Compared to the trend in magnitude of extreme precipitation, relatively more weather stations (50%-90%) showed increasing trend in the frequency of occurrence of daily extreme precipitation events (heaviest 1% daily precipitation).

These likely future changes in annual maximum precipitations underscore the need for non-stationary frequency analysis to represent the effects of climate change on IDF curves and corresponding engineering applications. More research is needed to rigorously identify and attribute trend and non-stationarity in storms. This is particularly important given the difficulty of distinguishing between low-frequency climate variability and long-term trend with the limited available precipitation records. In fact, identification of nonstationary precipitation patterns and their significance for the engineering analyses have been the primary challenge in adopting the concept of non-stationarity in the IDF curves. The ongoing progress in big data science and advance in data mining and pattern recognition methodologies, such as deep learning, have the potential to capture complex trends and their causal relationships with other variables. Only two climate models are considered in this study due to the high computational demand of the dynamic downscaling method. Evaluation of climate change impacts on storm events will benefit from incorporation of more climate models.

Stationary and Nonstationary IDF curves

Rainfall IDF curves covering storm durations from 1-hour to 10-day and return periods from 2-year to 500-year were developed for various military installations in the United States based on past precipitation records and multi-model prediction of future precipitation (2035-2064). IDF curves are widely used in infrastructure design and risk assessment, and the curves from this study have potential application in adapting infrastructure design and risk assessment to incorporate projected changes in extreme precipitation. Nonstationary IDF curves were developed by allowing the location parameters of the distributions to vary with time. The likelihood ratio test, which compares the performance of stationary and nonstationary distributions, indicates the potential presence systematic trends and the inadequacy of the traditional stationary IDF curves to represent

the combined past and future precipitation extremes. The likelihood ratio was also used to evaluate the potential roles of other climatological phenomena on storm dynamics. The storms from a few installations were affected by large-scale climate variability, such as MEI and NAO, while the storms from all the 13 installations were affected by annual average rainfall. However, due to the challenge of applying the return period concept to develop the IDF curves when the distribution is a function of annual average rainfall, in this study we only consider time as a covariate (or distributions as a function of time). Future research utilizing the annual mean rainfall in combination with time as covariates may further improve the IDF characterization of the combined past and future precipitation extremes.

Comparing the stationary and nonstationary IDF values, the storm magnitudes corresponding to longer durations increased for most of the installations with the increase being higher for the installations located in central and eastern part of the country. For the installations in the south and southwest, the storm magnitudes with sub-daily durations have decreased while they have increased for daily and longer durations.

Dynamic Downscaling and Bias-Corrected Future Climate Extreme Projections

Dynamical downscaling with WRF-RCM at high spatial and temporal resolutions of 12 km and 30 minutes provides a reasonable method for capturing extreme storm events that likely represent small-scale physical processes and is able to include orographic effects, land-sea contrast, and land surface characteristics. This approach is better suited to extreme value analysis for IDF curves determination. However, the computational need is very high for 180 year simulations.

This project evaluated most promising quantile mapping methods and developed the HQM bias correction method and data processing tool that correct extreme precipitations (top 1%) with extreme value theory and precipitations below 99% with modified quantile mapping. The performance evaluations indicate that this approach (1) improves the annual maximum series that is the base for IDF determination, (2) preserves the signals of future change projected by the WRF-RCM model, and (3) corrects seasonal variation for lower quantile precipitations. The multiple comparisons also suggest that bias correction is important before incorporating future projections into IDF determination and different bias methods will significantly affect IDF values.

Snow and Snowmelt Effects IDF Curves

The snowmelt modeling with UEB modeling tool identified two scenarios that will affect AMS. In Scenario 1, NOAA's precipitation records may represent snow contributing to snowpack instead of liquid water during winter at freezing temperature, resulting in decreased AMS. In Scenario 2, rain on snow under the warmer temperature in early spring could significantly increase amount of liquid water as rainfall + snowmelt instead of precipitation only. The snowmelt effect may change annual maximum from other seasons to early spring, which is found more often at Fort Drum site. The increased AMS results in higher IDF by average 22 % for 10-year event, 24 % for 50-year event, and 25% for 100-year event over 31 locations at Fort Drum. However, reduced IDFs were found more at Lewis McChord site.

The results of snowmelt modeling confirmed that the current IDF methodology significantly underestimated IDF values for Scenario 2 cases and overestimated for Scenario 1 cases. It is important to incorporate the processes of snowpack and snowmelt into the development IDF.

Runoff IDF curves

Both rainfall, runoff, and watershed data (land cover, slope and soil type) were analyzed to identify the underlying processes that are responsible for major flooding events in the 13 military installations. The results from the analyses were used to determine the hydrologic modeling approach suitable for the flood frequency analysis. The runoff IDF curves were constructed for some of our study sites using the HEC-HMS hydrological model with the Soil Moisture Accounting (SMA) method for simulating the rainfall excess. This approach allows using the rainfall IDF curves and reasonably account the soil moisture condition for estimating the corresponding runoff. Future research is needed to translate the information obtained from rainfall IDF curves (e.g. design storms) for the estimation the corresponding runoff and flood risks. One of the remaining challenges to estimate the runoff IDF values from the given rainfall IDF values is representation of soil moisture condition in the event-based hydrologic model approach.

Interactive Web-based GIS Interface and Geodatabase

We expect the web-based tool and project website to be engaging, intuitive, and understandable for planners at DoD bases, and other stakeholders. Similar results for new locations can readily be added to the database and system, or other related data or tools could be added as enhancements. The existing project website and tool can continue to be hosted after the current project schedule is complete with a modest budget to address software security updates and other needed activities, or they can be deactivated and an archive made available for future reference. The mapping tool can also evolve to serve more militaries bases with more information through ESTCP demonstrations in the upcoming years.

8. LITERATURE CITED

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9. APPENDICES

a. Supporting Data:

All the IDF results (figures and tabulated data) for historical precipitation data, combined historical and future precipitation data, IDF values with snow effect, and uncertainty ranges can be accessed and downloaded for our 13 military installations from the project website: <https://bogi.evs.anl.gov/dodewa/tool/index.html>.

b. List of Scientific/Technical Publications

- Ye, S., H. Li, L.R. Leung, J. Guo, Q. Ran, Y. Demissie, and M. Sivapalan, 2017. Understanding flood seasonality and its temporal shifts within the contiguous United States, *Journal of Hydrometeorology*. DOI: 10.1175/JHM-D-16-0207.1.
- Wang, W., H. Li, L.R. Leung, Y. Demissie, and G. Blöschl, 2017. Nonlinear filtering effects of reservoirs on the flood frequency curves at the regional scale, *Water Resources Research*. DOI: 10.1002/2017WR020871.
- Moges, E., A. Jared, Y. Demissie, E. Yan, 2018. Bayesian Augmented L-Moment Approach for Regional Frequency Analysis, *World Environmental and Water Resources Congress*, DOI: 10.1061/9780784481417.016
- Moges, E., A. Jared, Y. Demissie, E. Yan, R. Mortuza, and V. Mahat. Bayesian Augmented L-moment Approach for Regional Frequency Analysis, *Stochastic Environmental Research and Risk Assessment*. (in revision)
- Demissie, Y., MR. Mortuza, E. Yan, A. Jared, 2018. Drainage system and flooding risk under nonstationary climate and storm conditions, SERDP/ESTCP Symposium, Washington DC, Nov. 28 – 30.
- Yan, E., A. Jared, Y. Demissie, E. Moges, and MR. Mortuza, 2018. Development of next-generation intensity-duration-frequency curves under changing climate. AGU Fall Meeting, Washington DC, Dec. 10 – 14.
- Gebremichael, M., Y. Demissie, 2018. Urban Storm Water Management and Flooding under Extreme Precipitation Events in Seattle. AGU Fall Meeting, Washington DC, Dec. 10 – 14.
- Demissie, Y., MR. Mortuza, E. Yan, A. Jared, 2018. Current IDF Values and Drainage Designs in a Non-stationary Climate, AGU Fall Meeting, Washington DC, Dec. 10 – 14.
- Jared, A., E. Yan, Y. Demissie, MR. Mortuza, E. Moges, 2018. Development of New Intensity-Duration-Frequency Curves for a Changing Climate. AGU Fall Meeting, Washington DC, Dec.10-14.