# (1) EarthSystemScience <br> Extreme Precipitation in a Changing Climate: Ankara Case Study 

Middle East Technical University<br>Graduate School of Natural and Applied Sciences<br>Earth System Science (ESS) Interdisciplinary Program

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## Outline

- Motivation
$\square$ Objectives
- Methodology
$\square$ Observed Precipitation Data Analyses
$\square$ Projected Precipitation Data Analyses
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## Motivation: Climate Change

## Global Precipitation Change (For the last 2 decades and Projected Periods)



Low (RCP 2.6) ensemble average (dark line) and spread of ensemble members (shaded area). Values are for the model grid cell containing: $39.912^{\circ} \mathrm{N}$ $32.84^{\circ}$ E


High (RCP 8.5) ensemble average (dark line) and spread of ensemble members (shaded area). Values are for the model grid cell containing: $39.912^{\circ} \mathrm{N}$ $32.84^{\circ}$ E.

## Motivation: Climate Change and Extreme Events




Figure 1.1. Annual count of extreme events in Turkey in the period of 1940-2017

Figure 1.2. Distribution of extreme events and their types in Turkey in 2017

Annual count of extreme events in Turkey shows an increasing trend in 1940-2017 period (Climate Assessment 2017 Report, February 2018 - State Meteorological Service).

During 2017 most hazardous extreme events were; heavy rain/floods ( $\mathbf{3 1 \%}$ ), wind storm ( $\mathbf{3 6 \%}$ ), hail ( $\mathbf{1 6 \%}$ ), heavy snow (7\%), and lightning (4\%)

## Problem Statement

- Climate change in Turkey has been evaluated in many different studies with its different aspects. Majority of analysis performed and the future estimation works were focused on temperature and precipitation changes which are the most important climate parameters causing the extreme events.
- In the last decades, heavy rainfall and flash flooding caused various damages in Turkey; for example settlements were damaged, road transportation and vehicles are disrupted, and life was negatively affected in Ankara


## Objectives

- To analyze the rainfall extreme value frequencies for stationary and nonstationary conditions in Ankara region,
- To produce Return Levels in stationary and non-stationary conditions with observed data and future projections,.
- To figure out the superiority of nonstationary and stationary models to each other,


## Methodology and Data

The methodology of precipitation analysis in this study consists of;
(1) Trend analysis is carried out for observed (1950-2015) and projected data (2015-2098)
(2) Projected data is disaggregated into finer scales (5 min) and then it is aggregated to next analysis time scales (10, 15, and $30 \mathrm{~min}, \ldots$ )
(3) Stationary GEV (St) models are developed, return levels are derived for desired return periods considering single and multi-time periods for observed and single period for projected data
(4) Non-stationary GEV (NSt) models are developed, return levels are derived for desired return periods for observed and projected data
(5) Stationary and Non-stationary model results were compared

- Observed Data for Ankara - 1950-2015 (State Meteorological Services)
- Projected Data; Three global climate models (GCM) are used; namely HadGEM2-ES, MPI-ESM-MR and GFDLESM2M. These models are operated with the RCP 4.5 and RCP 8.5 emission scenarios - 2015-2098 (State Meteorological Services)


## Methodology



Figure 1.3. Rainfall Data Analyses Framework

## Observed Data



Figure 1.4. Sub-Hourly Time Series Trend

## Trends \& Change Point



Figure 1.5. Hourly Time Series Trend


Figure 1.6. Average annual maximum rainfall intensities (mm) for sub-hourly and hourly storm durations

## Observed Data



Figure 1.7. Storm Durations Used for Stationary Models

| Model | Location | Scale | Shape |
| :---: | :---: | :---: | :---: |
| NStGEV1 | $\mu \mathrm{t}=\beta 0+\beta 1 \mathrm{t}$ | $\sigma$ (constant) | $\xi$ (constant) |
| NStGEV2 | $\mu \mathrm{t}=\beta 0+\beta 1 \mathrm{t}$ | $\sigma \mathrm{t}=\beta 0+\beta 1 \mathrm{t}$ | $\xi$ (constant) |
| NStGEV3 | $\mu$ (constant) | $\sigma \mathrm{t}=\beta 0+\beta 1 \mathrm{t}$ | $\xi$ (constant) |
| NStGEV4 | $\mu \mathrm{t}=\beta 0+\beta 1$ temperature | $\sigma$ (constant) | $\xi$ (constant) |
| NStGEV5 | $\mu \mathrm{t}=\beta 0+\beta 1 \mathrm{t}$ | $\sigma \mathrm{t}=\beta 0+\beta 1 \exp (\mathrm{temperature})$ | $\xi$ (constant) |
| NStGEV6 | $\mu \mathrm{t}=\beta 0+\beta 1 \exp (\mathrm{temperature})$ | $\sigma \mathrm{t}=\beta 0+\beta 1 \exp (\mathrm{temperature})$ | $\xi$ (constant) |
| NStGEV7 | $\mu \mathrm{t}=\beta 0+\beta 1 \exp ($ temperature $)$ | $\sigma \mathrm{t}=($ constant $)$ | $\xi$ (constant) |
| NStGEV8 | $\mu$ (constant) | $\sigma \mathrm{t}=\beta 0+\beta 1$ temperature | $\xi$ (constant) |

Table 1.1. Non-stationary models with time and covariate (temperature) dependent location and scale parameters

|  | 2-year | 5-year | 10-year | 25-year | 50-year | 100-year | 200-year |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Mean Value Change |  |  |  |  |  |  |  |
| FiveMin | -4\% | -4\% | -5\% | -9\% | -11\% | -15\% | -18\% |
| TenMin | -14\% | -13\% | -12\% | -9\% | -7\% | -5\% | -3\% |
| FifteenMin | -1\% | -4\% | -6\% | -9\% | -12\% | -14\% | -17\% |
| ThirtyMin | 0\% | -3\% | -6\% | -10\% | -13\% | -16\% | -19\% |
| OneHour | -7\% | -5\% | -3\% | 0\% | 3\% | 6\% | 10\% |
| TwoHours | 0\% | -3\% | -4\% | -5\% | -6\% | -7\% | -7\% |
| ThreeHours | 0\% | -3\% | -5\% | -8\% | -11\% | -13\% | -16\% |
| SixHours | 1\% | -1\% | -2\% | -3\% | -4\% | -5\% | -5\% |
| Median Value Change |  |  |  |  |  |  |  |
| FiveMin | -3\% | -2\% | -4\% | -7\% | -9\% | -12\% | -15\% |
| TenMin | -13\% | -12\% | -10\% | -7\% | -4\% | -2\% | 0\% |
| FifteenMin | -1\% | -2\% | -4\% | -7\% | -9\% | -12\% | -14\% |
| ThirtyMin | 1\% | -2\% | -5\% | -8\% | -10\% | -13\% | -16\% |
| OneHour | -8\% | -5\% | -2\% | 2\% | 5\% | 8\% | 12\% |
| TwoHours | -1\% | -2\% | -3\% | -4\% | -4\% | -5\% | -5\% |
| ThreeHours | -1\% | -2\% | -4\% | -7\% | -9\% | -11\% | -14\% |
| SixHours | 0\% | -1\% | -2\% | -2\% | -3\% | -3\% | -4\% |

Table 1.2. Nonstationary GEV Best Fit Model Return Levels (mm) - Mean and Median Value Change with Respect to Stationary GEV Model 9

## Observed Data



Figure 1.8. Stationary and Best Fit Nonstationary Model Return Level (mm) Comparison - Return Period vs. Return Level

- The shorter the storm duration the larger the differences between the non-stationary and stationary extremes.
- Among the storm durations, only one hour time series exhibit larger values for its nonstationary model return level values, however this is not valid for shorter return periods such as 5 years or 20 years
- Sub-hourly storm durations indicate larger difference than hourly storm durations and non-stationary estimates are smaller than their corresponding stationary values


## Projected Data



Figure 1.9. Projected Storm Durations Used for Stationary Models for 2015-2098 period

## Projected Data: Trends



Figure 1.10. Projected 10-15 Minutes (a,b) and 1-6 Hours (c,d) Annual Maximum Time Series for 2015-2098

Projected Data

| Return Period <br> -Years | 2 | 5 | 10 | 25 | 50 | 100 | 200 | 2 | 5 | 10 | 25 | 50 | 100 | 200 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Model | Mean Value Change |  |  |  |  |  |  | Median Value Change |  |  |  |  |  |  |
| MPI45 | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% |
| MPI85 | 0\% | -1\% | -1\% | -2\% | -2\% | -2\% | -2\% | 1\% | 0\% | -1\% | -1\% | -2\% | -2\% | -2\% |
| GFDL45 | -1\% | -1\% | 0\% | 0\% | 1\% | 1\% | 2\% | 1\% | 1\% | 1\% | 1\% | 2\% | 2\% | 3\% |
| GFDL85 | 1\% | 0\% | 0\% | -1\% | -1\% | -2\% | -2\% | 2\% | 2\% | 2\% | 2\% | 2\% | 2\% | 1\% |
| HG45 | 0\% | -1\% | 0\% | 1\% | 2\% | 2\% | 4\% | 0\% | -1\% | 0\% | 1\% | 2\% | 2\% | 4\% |
| HG85 | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 1\% | -1\% | -1\% | -1\% | -1\% | 0\% | 0\% | 0\% |
| Mean Value Change |  |  |  |  |  |  |  | Median Value Change |  |  |  |  |  |  |
| MPI45 | 0\% | 0\% | 0\% | 0\% | 1\% | 2\% | 3\% | 0\% | 0\% | 0\% | 1\% | 1\% | 2\% | 3\% |
| MPI85 | 0\% | -1\% | -1\% | -2\% | -2\% | -2\% | -3\% | 1\% | 0\% | -1\% | -1\% | -2\% | -2\% | -2\% |
| GFDL45 | -1\% | -1\% | -1\% | 0\% | 0\% | 0\% | 1\% | -1\% | -1\% | -1\% | 0\% | 0\% | 0\% | 1\% |
| GFDL85 | 0\% | 0\% | -1\% | -1\% | -1\% | -1\% | -1\% | 0\% | 0\% | 0\% | 0\% | -1\% | -1\% | -1\% |
| HG45 | -1\% | -1\% | 0\% | 2\% | 3\% | 5\% | 6\% | -1\% | -1\% | 0\% | 2\% | 3\% | 5\% | 6\% |
| HG85 | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 1\% | -2\% | -1\% | -1\% | -1\% | -1\% | 0\% | 0\% |
| Mean Value Change |  |  |  |  |  |  |  | Median Value Change |  |  |  |  |  |  |
| MPI45 | -1\% | -1\% | -1\% | -1\% | -2\% | -2\% | -2\% | -1\% | -1\% | -1\% | -1\% | -2\% | -2\% | -2\% |
| MPI85 | 0\% | -2\% | -2\% | -1\% | -1\% | 0\% | 1\% | 1\% | -1\% | -2\% | -1\% | 0\% | 1\% | 2\% |
| GFDL45 | -1\% | 0\% | 0\% | 1\% | 2\% | 3\% | 4\% | -1\% | 0\% | 0\% | 1\% | 2\% | 3\% | 4\% |
| GFDL85 | 0\% | 0\% | -1\% | -2\% | -3\% | -3\% | -4\% | 2\% | 2\% | 1\% | 1\% | 0\% | 0\% | -1\% |
| HG45 | 0\% | -1\% | -1\% | 0\% | 0\% | 0\% | 1\% | 0\% | -1\% | -1\% | 0\% | 0\% | 0\% | 1\% |
| HG85 | 0\% | -1\% | -1\% | -1\% | -1\% | -1\% | -1\% | -3\% | -3\% | -2\% | -2\% | -2\% | -2\% | -2\% |
| Mean Value Change |  |  |  |  |  |  |  | Median Value Change |  |  |  |  |  |  |
| MPI45 | 0\% | -1\% | -1\% | -2\% | -2\% | -3\% | -4\% | 0\% | -1\% | -1\% | -2\% | -2\% | -3\% | -4\% |
| MPI85 | 2\% | 2\% | 1\% | 0\% | 0\% | -1\% | -2\% | 2\% | 3\% | 3\% | 3\% | 3\% | 2\% | 2\% |
| GFDL45 | 1\% | 0\% | -2\% | -5\% | -7\% | -10\% | -13\% | 1\% | -1\% | -3\% | -6\% | -9\% | -12\% | -15\% |
| GFDL85 | 0\% | -2\% | -3\% | -5\% | -7\% | -9\% | -12\% | 1\% | 0\% | -1\% | -3\% | -4\% | -5\% | -7\% |
| HG45 | 0\% | -1\% | -3\% | -5\% | -7\% | -9\% | -11\% | 2\% | 2\% | 1\% | -1\% | -2\% | -4\% | -6\% |
| HG85 | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% | 1\% |



Table 1.4. Nonstationary Model-Stationary Comparison for Projected Data - Average Values

Table 1.3. Nonstationary Mean and Median Value Change with Respect to Stationary Model - Projected Data

## Projected Data

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Figure 1.11. Stationary Model Results for Projected Time Series

## Projected Data



Figure 1.12. 10-15 Minutes and 1-6 Hours Ensemble Model Comparison for Projected Data
On average nonstationary models produce mostly lower return levels for mid and longer return periods for all durations and similar results for short ( 2 and 5 years) return periods except one hour storm duration.

## Projected Data



Figure 1.15. Ten Minutes Data Model Comparison - Best Fit Nst and St for Observed and Projected Data and SMS (State Meteorological Service) Bata

Projected Data


Figure 1.16. Fifteen Minutes Data Model Comparison - Best Fit Nst and St for Observed and Projected Data and SMS (State Meteorological Service) Data

Projected Data


Figure 1.17. One Hour Data Model Comparison - Best Fit Nst and St for Observed and Projected Data and SMS (State Meteorological Service) Datầ

Projected Data


Figure 1.18. Six Hours Data Model Comparison - Best Fit Nst and St for Observed and Projected Data and SMS (State Meteorological Service) Datâ

## Summary and Conclusions:

- Stationary GEV models were capable of fitting extreme rainfall data for all durations but the developed non-stationary GEV models showed advantage over the stationary models
- The differences in design rainfall estimates between two time slice, entire period and nonstationary assumption models support the need to update the current information, with the most recent data and approaches.
- The differences also reveal the need to conduct analysis using future climate data.
- Nonstationary model results are in general exhibited smaller return level values with respect to stationary model results of each storm duration for the observed data driven model results.
- On average nonstationary models produce mostly lower return levels for mid and longer return periods for all durations and similar results for short ( 2 and 5 years) return periods except one hour storm duration for the projected data.
- Almost all the nonstationary model maximum return level results are significantly higher than stationary model maximum return level results for all storm durations and return periods for the projected data driven model results.


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