Disaggregation of Future Regional Climate Model Data to Generate Future Rainfall Intensity-Duration-Frequency Curves to Assess Climate Change Impacts

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Disaggregation of Future Rainfalls to Generate IDF Curves

Abstract

Heavy increase in urbanization, industrialization and population is causing an increase in emissions of greenhouse gases (GHG) and this causes variations in atmosphere. Climate change causes extreme rainfall events and these events are expected to be enhanced in the future. Since flooding is influencing urban areas, controlling and management of flooding is a major necessity. Intensity-Duration-Frequency (IDF) curves play a huge role in representing rainfall characteristics by linking intensity, duration, and frequency of rainfall.

Analysing short-duration rainfall is crucial for urban areas due to fast responses of drainage systems against heavy rainfall events. IDF curves were generated via the Gumbel method for rainfalls from 5-min to 24-h in this study. However, providing short-duration rainfall data is challenging due to the low capacity, costs and geographic conditions. Therefore, the HYETOS disaggregation model was applied to obtain sub-hourly data.

IDF curves are stationary since they only consider historical events. However, IDF curves must be non-stationary and time varying based on preparation for upcoming extreme events. This study aims to generate IDF curves under climate change scenarios. The Regional

Climate Model (RCM) HadGEM2-ES generated under Representative Concentration Pathways (RCP) 4.5 and 8.5 scenarios and was used in the study to represent future rainfalls. Future daily rainfalls were disaggregated into sub-hourly using disaggregation parameters of corresponding station's historical rainfall data since it is impossible to estimate parameters when hourly data is not available. With this new approach, future daily rainfall data is disaggregated into 5-min data by complying with historical rainfall patterns rather than complying with randomly selected rainfall characteristics. The study concluded that future rainfall intensities increases compared to historical IDF curves. RCP8.5 scenarios have higher rainfall intensities for all return periods compared to RCP4.5 scenarios for all stations except a station. In addition, the accuracy of the selected disaggregation model was verified.

Keywords: IDF curves, disaggregation, climate change, RCM, RCP, flood

1. INTRODUCTION

Irrepressible growth of industrial activities, urbanization and population enhance greenhouse gases (carbon dioxide, methane, aerosols etc.) emissions. This enhancement causes major variations in climate and leads to a necessity to deal with a serious challenge in the future: climate change (Mirhosseini, Srivastava, & Stefanova, 2013). Climate change causes global warming by increasing global temperatures, and this causes enhancement of evapotranspiration and water vapour in the atmosphere, hence, more extreme events such as extreme rainfall. Extreme rainfall events are one of the most serious consequences of these changes and they can cause floods. Floods damage to structures such as sewers, drainage systems, bridges, and infrastructures (Singh, Arya, Taxak, & Vojinovic, 2016). Dealing with heavy rainfall events that cause floods, loss of life, crops, and properties, is challenging for urban areas. High intensity rainfall events are considered a key factor in flooding events. Rainfall Intensity-Duration-Frequency (IDF) curves are necessary in designing hydraulic structures such as sewers, drainages, gutters, and culverts since an inappropriate design can lead to losses of life, economy and property (Burn, 2014). Using IDF curves to design water facilities allows engineers to be ready for extreme events. Thus, possible damages can be decreased. IDF curves are widely applied in many water related projects, flood forecasting and management and water management (Simonovic & Peck, 2009).

IDF curves give a rainfall intensity for the selected duration and return period. These IDF curves demonstrate the possibility of occurrence of a rainfall event for a specific duration. Durations can vary between 5 minutes and 24 hours. Ordinarily, short-duration (high-resolution) rainfalls (e.g., from 5 min to 30 min) are analysed for urban areas, whereas longer duration (low-resolution) rainfalls (e.g., from 1 hour to 24 hours) are applied for rural areas (Bougadis & Adamowski, 2006). Urban floods, especially flash floods, are the typical consequence of the fast responses by drainage systems (Forestieri et al., 2017). Therefore, analysing short-duration rainfalls is crucial for urban areas due to fast responses of drainage systems against heavy rainfall events (Nhat, Tachikawa, Sayama, & Takara, 2008). Even though long-duration data can be provided from rain gauge stations and climate models easily, providing short-duration rainfall data is challenging due to the limitations of a station's capability, costs and geographic conditions. Even if short-duration rainfall data is obtained, they are usually scarce and not reliable. Hence, it is mandatory to apply a process called "disaggregation" to overcome these limitations. There is a large volume of disaggregation methods and studies describing disaggregation. K-nearest neighbour (KNN) developed by Prairie, Rajagopalan, Lall, and Fulp (2007), HYETOS developed by

Koutsoyiannis and Onof (2001), and Multivariate Rainfall Disaggregation (MuDRain) developed by Koutsoyiannis (2003) models have been used widely (Debele, Srinivas, & Parlange, 2007; Hanaish, Ibrahim, & Jemain, 2011; Lu & Qin, 2013). Rodriguez-Iturbe, Cox, and Isham (1987) developed the Bartlett-Lewis disaggregation model to disaggregate daily and hourly rainfall into sub-hourly (e.g., 5-min). Afterwards, a disaggregation model HYETOS based on Bartlett-Lewis model was established by Koutsoyiannis and Onof (2001). The HYETOS model allows users to obtain short-duration rainfalls from long-duration rainfalls by benefitting from four statistical values of 1, 6, 12 and 24-h rainfall data (mean, variance, auto-covariance lag 1 and proportion of dry days).

To generate IDF curves, annual maxima for rainfalls are obtained for each duration. Afterwards, probability distribution functions such as Gumbel, Generalized Extreme Value (GEV), the Log-Normal and Log Pearson Type III are applied to annual maxima to obtain rainfalls for each return period. Computed rainfalls (mm) are converted to rainfall intensities (mm/h). Many researchers generated and studied on IDF curves since 1930s (Sherman, 1931; Bernard, 1932; Hershfield, 1961; Bell, 1969; Chen, 1983; Burn & Taleghani, 2012; Van de Vyver, 2018; Nwaogazie & Sam, 2019).

Although IDF curves based on historical rainfall events are used frequently, they are still not fully sufficient against a rapidly changing environment. Historical rainfall-based IDF curves are stationary, therefore they are ineffective in catching climate change conditions (Singh et al., 2016). Current IDF curves assume that extreme rainfall events will not change under future climate conditions. Hence, developing advanced IDF curves, which are successful at representation of both historical and future climate conditions, is a huge necessity. With this type of IDF curves, it is possible to deal with extreme rainfall events under non-stationary climate conditions. Many studies have been performed to update IDF curves considering future conditions (Mirhosseini et al., 2013; Liew, Raghavan, & Liong, 2014; Hajani, 2020). In the study of Zhu, Stone, and Forsee (2012), they investigated the generation of IDF curves that were affected by rainfall intensity changes under SRES-A2 greenhouse emission scenario. Rainfall intensities with 3-h intervals obtained from compounds of Regional Climate Models (RCMs) and Global Climate Models (GCMs) were used in the study. IDF curves were developed for single station locations and calculated annual maximum series for 3, 6, 9, 12, 18, 24, 48 and 96 hours. De Souza Costa, Blanco, and de Oliveira-Junior (2020) performed a study on IDF curves under future climate conditions. They used three different Global Climate Models (GCMs) under Representative Concentration Pathway (RCP) scenarios RCP4.5 and RCP8.5.

This study generates historical IDF curves and updated IDF curves based on disaggregated rainfalls to assess climate change impact on rainfall intensities. (5, 10, 15, 30 minutes; 1, 2, 3, 4, 5, 6, 8, 12, 18 and 24 hours) for durations, (2, 10, 25, 50 and 100 years) for return periods were selected. Eight meteorological stations from Istanbul, Turkey were selected as study areas. Gumbel function was selected as a frequency analysis technique to generate IDF curves from annual maximum rainfalls. RCMs generated under RCP scenarios RCP4.5 and RCP8.5 were provided for the period of 2021-2099. to be used as daily future rainfall data. HadGEM2-ES developed by the Met Office Hadley Centre Institute (MOHC) was selected as the RCM. Unfortunately, RCMs are not suitable to use directly due to biases between observed and simulated historical rainfall data. Therefore, the distribution mapping method was applied to correct these biases. Provided future rainfall events were in daily form, hence, the HYETOS model was applied for the disaggregation of daily future rainfall into sub-hourly and hourly rainfall to generate IDF curves, which is generated by rainfalls in the range of 5-min and 24-h. Observed rainfall data provided by the Turkish State Meteorological Service (TSMS) contains different 1-min and hourly rainfall data sets. The HYETOS model was also applied for the disaggregation of observed hourly rainfall data provided by the TSMS into sub-hourly rainfall to generate historical IDF curves. As mentioned before, HYETOS parameters are computed if hourly rainfall data exist. However, providing and dealing with future hourly data for long periods (e.g., 80 years for 2021-2099) is thorny due to huge amounts of data. If the aim is to generate short-duration future IDF curves, short-duration future rainfall should be obtained. Therefore, this study focuses on the disaggregation of future daily rainfall data. Since the data are daily, it is impossible to compute the parameters for future data. Therefore, the monthly parameters of each station's historical data were used for corresponding station's future data. R Studio was employed from the beginning of the study for all computations, analyses and plottings.

This study has three objectives: (i) generating more reliable and effective future IDF curves under various climate change scenarios for urban areas by evaluating short-duration future rainfall data for drainage and infrastructure systems, (ii) disaggregation of future daily rainfalls into sub-hourly rainfalls with a new approach to HYETOS disaggregation model, (iii) verifying the accuracy of the selected model by comparing IDF curves generated by disaggregated and observed rainfalls for the corresponding stations. This new approach includes applying historical monthly disaggregation parameters of each station to corresponding station's future data. This process gives a chance for future data to capture historical patterns of rainfall as much as possible for each station during the disaggregation process. Hence, the method is valid when hourly future data are scarce due to various reasons. The final objective is to assess the impact of climate change impact on rainfall intensities by comparing historical and future IDF curves and IDF curves under RCP4.5 and RCP8.5 scenarios with each other.

2. DATA AND METHODS

2.1 Study Area

The study area Istanbul is located in north-western Turkey (Figure 1). The city is located in the Marmara region with a total area of 5,343 km2 and a population of 15,519,267. The geographical location of the city is 41°00′49″N 28°57′18″E. One of the most important characteristics of this city is that it separates Europe and Asia. Thus, the city has lands in both Europe and Asia. The Black Sea and the Marmara Sea are connected in Bosphorus. Istanbul has the highest population in Turkey and Europe. Camlica Hill is the highest point of the city with an altitude of 288 m. Rainfall and IDF curve data were provided for eight different meteorological stations managed by the TSMS in Istanbul. Thus, studies were performed for the selected stations, and future climate data obtained from RCM were generated for each station. Three stations are on the Asian side, and five stations are on the European side. The stations are listed as follows: Canta, Terkos, Olimpiyat, Omerli, Florya, Sariyer, Goztepe, and Sile (Figure 2).

2.2 Data Types

2.2.1 Observed Data

To generate IDF curves with the effects of climate change in the future, both observed rainfall and future climate data simulated under climate change scenarios are needed. In this study, observed, simulated historical and simulated future rainfall data and historical IDF curve data were used. 14 years (2005-2018) observed rainfall data (mm) were provided by the TSMS for 8 different stations. Stations listed in the previous section were: Canta, Terkos, Olimpiyat, Florya, Sariyer, Goztepe, Omerli, and Sile. For Omerli, Terkos, Canta, and Olimpiyat stations, 1-minute rainfall data were provided. For other stations, hourly rainfall data were provided. These data were used for three reasons: (i) to verify that the disaggregation process was applied correctly, (ii) to obtain Hyetos disaggregation parameters that will later be used in the disaggregation of simulated future rainfall, (iii) to generate historical IDF curves for all stations. IDF curves generated by observed rainfall provided by the TSMS were used to make a comparison of both future IDF curves and IDF curves generated from disaggregated historical rainfall. IDF curves were available for stations Florya, Goztepe and Sariyer.

2.2.2 Regional Climate Model (RCM)

Climate models are the representation of the climate system under climatic scenarios to understand climate change in the future. These models can be divided into GCMs and RCMs. Both GCMs and RCMs are constructed under different RCP scenarios for various climate components such as rainfall, temperature, wind, etc. High-resolution RCMs represent truthful simulations of heavy rainfall compared to GCMs. Therefore, RCMs are preferable for water management projects. (Mailhot, Duchesne, Caya, & Talbot, 2007). Both simulated historical and simulated future data were obtained from the Earth System Grid Federation (ESGF) – Lawrence Livermore National Laboratory (LLNL) website. Simulated daily historical rainfall data for the period of 1949-2005 were provided. Simulated daily future rainfall data were provided for 2021-2099 under RCP4.5 and RCP8.5 scenarios.
The Intergovernmental Panel on Climate Change (IPCC) published the Fifth Assessment Report (IPCC 2014) to assess climate change in the future using RCP scenarios. RCPs are used to define emissions of air pollutants, greenhouse gases, and atmospheric concentrations. Watts per square meter (W/m2) is the unit which represents energy imbalance in the atmosphere. Radiative forcing is 4.5 W/m2 for RCP4.5 and 8.5 W/m2 for RCP8.5 (Padhiary, Patra, Dash, & Kumar, 2020). In terms of rainfall intensities, the magnitudes are listed as follows from the lowest to the highest: RCP2.6, RCP4.5, RCP6.0, and RCP8.5 (Singh et al., 2016).
The selected RCM was from the Coordinated Regional Climate Downscaling Experiment (CORDEX) Europe program. Model HadGEM2-ES with a 12.5 km resolution developed by the MOHC was preferred. Outputs from HadGEM2-ES were downscaled to each station. Distribution mapping was preferred as bias-correction methods to handle biases between observed and simulated historical data.

2.2.3 Climate Forecast System Reanalysis (CFSR)

As mentioned in previous sections, RCMs are not available to use directly due to biases between observed and simulated historical data. To correct these biases, the Climate Model

Data for Hydrologic Modeling (CMhyd) tool was applied (Rathjens, Bieger, Srinivasan, Chaubey, & Arnold, 2016). Using the CMhyd tool, RCMs were downscaled to each meteorological station to study with finer-scale climate data. Simulated historical data, observed data, and simulated future data were used together for the bias-correction process. As observed data to be used in the bias-correction process, daily rainfall for the period of 1979-2014 was obtained from the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) for each station. The CFSR is a reanalysis service which combines observations made in the past by weather stations with today's weather model to provide a complete picture of past rainfall events. Missing values are recreated by blending overlapping existing values from the observed data. CFSR data were preferred since the observed data provided by TSMS have some missing values. Simulated historical RCM data were provided for the period of 1949-2005, therefore, it was necessary to overlap periods of historical RCM data and observed data as much as possible. Observed data provided by the TSMS was insufficient to overlap RCM data since the data is from 2005 to 2018 and the period of historical RCM data is 1949-2005. The study of El Afandi (2014) concluded that the CFSR can be used when there are lacks in observed data sets since the discrepancies between observed and CFSR data are too small. The CFSR rainfall data can be considered as an alternative for data-scarce regions (Cuceloglu & Ozturk, 2019). Used data types are demonstrated in Figure 3.

2.3 Bias-Correction of Simulated Data

The RCM has disadvantages to use directly as climate data in hydrological studies. RCM outputs are not suitable to be used directly without correcting their biases. These biases arise due to inconsistencies between observed and simulated historical rainfall (Rathjens et al, 2016). Observed high rainfall and the number of dry days is not well represented if biases exist. Seasonal alterations and extreme temperatures are predicted badly due to biases. RCMs simulate low rainfall days instead of dry days (Teutschbein & Seibert, 2010). The CMhyd software developed by Texas A&M University (TAMU) which is available online was preferred for the bias-correction process. The general framework of the bias-correction process was described by Rathjens et al. (2016) in Figure 4. First, biases between observed climate data and simulated historical climate data are identified and the bias-correction algorithm is then parameterized. This algorithm is then applied to simulated future climate data to correct biases. As a result, corrected historical and future climate data are obtained as output. Bias-correction helps users to use RCMs or GCMs in hydrological studies by representing simulated data better. Several bias-correction methods, including distribution mapping, were developed in the study of Teutschbein and Seibert (2010). In this study, the distribution mapping method was employed as the bias-correction method.

2.3.1 Distribution Mapping

Teutschbein and Seibert (2010) applied this method in their studies. "Probability mapping", "quantile matching", "statistical downscaling", and "histogram equalization" terms can be used for distribution mapping in the literature. With the distribution mapping, the distribution function of simulated climate data is corrected to coordinate with the distribution function of observed data. To perform this, a transfer function is used to shift the distribution of simulated data. It is assumed that the biases are stationary under climate change for this method (Teutscbein & Seibert, 2010). Distribution mapping employs Gamma distribution to remove biases. Thom (1958) expressed the Gamma distribution with shape parameter k, and scale parameter β. Gamma distribution is applicable to the distribution of rainfall (Teutscbein & Seibert, 2010).

$$f_y = \frac{1}{\beta^k \Gamma(k)} x^{k-1} e^{-x/\beta} \; ; \; x \geq 0; \; \beta, k > 0 \tag{1}$$

Where β is the scale parameter, k is the shape parameter, Γ is the gamma function, and x is normalized daily rainfall. Each grid and month have its own scale and shape parameter. With this method, mean, variance, skew, and frequency of rainfall events are corrected. The distribution profile is managed by shape parameter k. Three circumstances are considered by the value of k. When $k < 1$, it defines exponentially shaped Gamma distribution, $k = 1$ describes exponential distribution, $k > 1$ indicates a skewed uni-modal distribution. The scale parameter β dictates dispersion of the Gamma distribution. $k > 1$ situation is commonly applied for observed daily rainfall. If the scale parameter β is small, it eventuates to a more compressed distribution, and this ends up with lower probabilities of extreme rainfall. If the β is large, this causes a stretched distribution, and this is the reason for higher probabilities of extreme events (Teutscbein & Seibert, 2010). The study by Teutschbein and Seibert (2010) showed that gamma distribution parameters fitted to simulated climate data showed similar patterns for the selected catchments in the study area. They reported that the level of commitment of the distribution parameters (k/β) defines the skill for the RCM to reproduce rainfall. As mentioned before, Teutschbein and Seibert (2010) compared several bias-correction methods including linear scaling, local intensity scaling, power transformation, variance scaling, and distribution mapping considering the skills of methods to arrange the statistics of the respective observed climate data. The study concluded that distribution mapping is the best performing method for rainfall with the minimum MAE (minimum absolute error). They also concluded that the method is applicable to both current and future climate data.

2.4 Disaggregation of Daily and Hourly Rainfalls into Sub-Hourly Rainfall

Hydrological studies such as generating IDF curves require high-resolution rainfall data. This need arises from the fact that maximum values of finer scales of observed rainfall (e.g., sub-hourly and hourly) are necessary to develop an IDF curve. However, providing high-resolution data is challenging due to the limitations of a station's capability, costs and geographic conditions. To cope with this shortcoming of finer scale rainfall data, disaggregation methods which derive finer scale data (i.e. hourly and sub-hourly) from coarser-scales (i.e. daily data) are applied.

As in past studies, high-resolution rainfall was needed in this study. IDF curves are generated using maximum values of sub-hourly rainfall (in the range of 5 to 30 minutes) and hourly data (i.e., from 1 to 24 hours). Four stations with 1-minute rainfall data were provided, however there is still a lack of sub-hourly data for the stations of Florya, Goztepe, Sile, and Sariyer. Hourly rainfall data were provided for these four stations for 2005-2018. The disaggregation process was used for two purposes in this study (i) to disaggregate hourly historical rainfall data to sub-hourly data, (ii) to disaggregate daily future climate data simulated from RCMs to sub-hourly and hourly data.

(Koutsoyiannis & Onof, 2001) developed a computer programme called Hyetos based on the Bartlett-Lewis model, and they implemented a disaggregation scheme in an R package called "HyetosMinute". The Bartlett-Lewis model was constructed by Rodriguez-Iturbe et al. (1987) to overcome the inefficiency of simple Poisson models. In this study, Hyetos disaggregation model was applied.

The original Bartlett-Lewis model has 5 parameters (β, γ, μ_x, η, λ) for the disaggregation process. Storm origins are developed by λ, cell origins are developed by β, cell arrivals end after a specific time, and the time is exponentially distributed with γ. Each cell has a duration exponentially distributed with η. Uniform intensity for each cell is distributed exponentially with μ_x. Hanaish et al. (2011) explained the original Bartlett-Lewis rectangular pulses model in their study.

Rodriguez-Iturbe, Cox, and Isham (1988) adjusted the original model to boost the flexibility of the model to generate larger diversity of rainfall. This modified model is called Modified

Modified Bartlett-Lewis Rectangular Pulse Model (MBLRPM). With Gamma distribution, η is changed for each storm.

In this model, β and γ also altered, therefore ratios $k=\beta/n$ and $\varphi=\gamma/\eta$ stay constant. So that MBLRPM model has 6 parameters (α, φ, μ_x, k, λ, v). An enhanced version of the Evalutionary Annealing-Simplex Method is applied to estimate Bartlett-Lewis model parameters. 4 historical statistical values (mean, variance, auto-covariance lag-1, and the proportion of dry days) for 1-, 6-, 12- and 24-hour time scales of rainfall data are used to perform the estimation. MBLRPM parameters are used for single site disaggregation as inputs. Each month has its own parameters for the disaggregation process. Bartlett-Lewis parameters cannot be calculated for future data due to the absence of hourly future rainfall data. Therefore, parameters obtained for observed rainfall data were used for corresponding station's future monthly data. For example, parameters were calculated for each month of observed rainfall data of Florya station. Afterwards, these parameters were used for the disaggregation process of future rainfall data of Florya station for the corresponding months. Thus, each station has its own parameters for future rainfalls. The aim in doing this was to adapt to historical patterns of rainfall as much as possible for each station.

For the assessment of accuracy of the selected disaggregation method Hyetos, a comparison was performed between the historical IDF curves provided by the TSMS and IDF curves generated using observed hourly and sub-hourly historical data that disaggregated from the observed hourly rainfall provided by the TSMS. Results showed that IDF curves were in close relationship, so that MBLRPM was successful for the disaggregation. As mentioned before, MBLRPM was applied to disaggregate observed hourly rainfall into sub-hourly rainfall and disaggregate simulated daily future rainfall into sub-hourly and hourly to generate future IDF curves

2.5 Generating Historical and Future IDF Curves

This study focuses on generating IDF curves for both historical and future rainfalls. Periods of 2, 5, 10, 25, 50 and 100-year were selected as return period and for the durations, 5-, 10-, 15-, 30-min, and 1-, 2-, 3-, 4-, 5-, 6-, 8-, 12-, 18- and 24-h were selected.

The RCMs generated under RCP4.5 and RCP8.5 climate change scenarios were used to generate future IDF curves. On the other hand, observed rainfall data were used for historical IDF curves. Generating IDF curves requires annual maximum rainfall value for each duration (5-, 10-, 15-, 30-min, and 1-, 2-, 3-, 4-, 5-, 6-, 8-, 12-, 18- and 24-h) of both historical period (2005-2018) and future period (2021-2099). Historical 1-min data were aggregated to 5-, 10-, 15-, 30-min, and 1-, 2-, 3-, 4-, 5-, 6-, 8-, 12-, 18- and 24-h for Terkos, Omerli, Canta and Olimpiyat stations. Hourly historical data were disaggregated into 5-min rainfalls for Florya, Goztepe, Sariyer and Sile stations. Afterwards, 5-min rainfalls were aggregated to durations from 5-min to 24-hours. Future Similarly, future daily rainfall data were disaggregated into 5-min data and then aggregated. After rainfall data for all selected durations were obtained, annual maximum rainfall values were computed for each duration.

Probability distribution functions (PDF) are used to generate IDF curves. IDF curves were generated using the Gumbel distribution. The major advantage of the Gumbel distribution is its easy application and its use for only extreme events. Gumbel has two parameters: location and scale. The function of Gumbel is defined as:

$$F(x) = \frac{1}{\beta} e^{\frac{x-\alpha}{\beta}} e^{-e^{\frac{x-\alpha}{\beta}}} \tag{2}$$

Where α is the location, and β is the scale parameter. In this study, Method of Moments (MoM) was applied for the estimation of the parameters. Calculating rainfall intensities requires a Gumbel frequency factor for each return period. The mean and standard deviation of annual maximum values for each duration are then calculated. The Gumbel frequency factor K_T is calculated using the equation (Nwaogazie & Sam, 2019):

$$K_T = \frac{\sqrt{6}}{\pi}\left[0.5772 + \ln\left[\ln\left[\frac{T}{T-1}\right]\right]\right] \tag{3}$$

Where T is the return period.

The value of random variable R, which is rainfall (mm) for this study, was found with the equation given by Chow (1951):

$$R_T = M + K_T S \tag{4}$$

Where R is rainfall (mm), M and S are mean and standard deviation of observed maximum rainfall for the current duration, respectively, and K_T is the Gumbel frequency factor for each return period. Hence, rainfall values are calculated for the current duration at different return periods. Rainfall intensity I (mm/h) can be calculated by dividing rainfall R by selected duration d (hours).

$$I = \frac{R_T}{d} \tag{5}$$

Then, the process is performed for each duration and maximum rainfall intensities are obtained for each duration and for each return period.

Briefly, the steps to generate IDF curves are followed:

1. Annual maximum values of rainfall data for each duration (5-, 10-, 15-, 30-min, and 1-, 2, 3-, 4-, 5-, 6-, 8-, 12-, 18- and 24-h) and year (2005-2018 and 2021-2099) are calculated.
2. MoM was applied to obtain Gumbel parameters.
3. Gumbel frequency factors are derived for each return period.
4. Mean and standard deviation values are calculated for observed maximum rainfall values for each duration.
5. Rainfall values are computed with Chow's equation and rainfall intensity is calculated by dividing rainfall into durations.
6. The process is repeated for each duration.
7. IDF curves are plotted with calculated rainfall intensities for each duration and each return period.

3. RESULTS

This chapter contains three sections to show results of analyses of IDF curves. Differences quantified by percentage between IDF curves were determined. The first section contains the comparisons of IDF curves generated by the disaggregated rainfalls and IDF curves provided directly by the TSMS. These comparisons were performed to verify the accuracy of the disaggregation process. The second section displays the generated IDF curves for singular data: historical and future rainfalls of RCP4.5 and RCP8.5. This section is created to exhibit differences between historical and future climate conditions. Accordingly, historical IDF curves and future IDF curves generated for both RCP4.5 and RCP8.5 scenarios were compared separately. Section 3, the final section of the results chapter displays the differences between future IDF curves RCP4.5 and RCP8.5 to prove the impacts of different climate scenarios on rainfall.

3.1 Performance of the Disaggregation Model

IDF curves generated by observed rainfall for Florya, Sariyer and Goztepe stations were supplied by the TSMS to evaluate the performance of Hyetos disaggregation model. For the evaluation, the observed IDF curves were compared to the disaggregated IDF curves generated by the rainfall disaggregated from the hourly observed data. Initially, hourly observed rainfall data were disaggregated into sub-hourly data (5-, 10-, 15- and 30-min). Rainfall of hourly and greater time durations (1-, 2-, 3-, 4-, 5-, 6-, 8-, 12-, 18- and 24-h) were obtained by the aggregation of disaggregated 5-min rainfall data rather than the aggregation of hourly rainfall data provided by the TSMS. After obtaining all disaggregated rainfall data for all durations, IDF curves were generated using the Gumbel distribution method. Both disaggregated and observed IDF curves were plotted together to exhibit the accuracy of disaggregation method and to prove that IDF values are in close relationship. Percentage difference between total values of observed and disaggregated IDF curves is 2.36% for Florya, 2.98% for Goztepe and 3.04% for Sariyer station. These comparisons revealed that there is a positive correlation between observed and disaggregated rainfall intensities by 2.8% total average change when all stations considered. Since the selected disaggregation model shows a good performance to obtain sub-hourly data from hourly/daily data, the process was applied for the disaggregation of daily future rainfall data, as well. IDF curve trends for observed and disaggregated rainfall data for three stations are demonstrated in Figure 5. In addition, the percentage differences between IDF curves of disaggregated and observed rainfalls for each duration and return period are written in Table 1, Table 2, and Table 3 for Florya, Goztepe, and Sariyer stations, respectively.

3.2 Changes in Rainfall Intensities under Future Climate Conditions

This section deals with the variations of future IDF curves (2021-2099) with respect to historical (2005-2018) IDF curves. Analyses showed that both RCP4.5 and RCP8.5 scenarios have similar rainfall intensity trends. 588 rainfall intensity values exist for each RCP scenarios which are the multiply of 14 durations, 6 return periods, and 7 stations (RCP4.5 analyses for Omerli and RCP8.5 analyses for Canta do not exist due to uncorrectable biases). Most of these rainfall intensities are increasing in terms of number of values for RCP4.5 and RCP8.5 scenarios with respect to historical rainfall intensities with a value of 95.4% (561 of 588 is increasing) and 98.30% (578 of 588 is increasing), respectively. Rate of increase in terms of total value of rainfall intensities under RCP4.5 is 36.5%, and under RCP8.5 is 42.3%. For the RCP4.5 scenario, the observed highest increase in terms of value of a specific rainfall intensity is 79.7% for Canta station for the duration of 24-h and a return period of 2-y, and the highest decrease is -25% for Olimpiyat station for the duration of 2-h and a return period of 100-y. For the RCP8.5, the highest increase is %74 for Omerli station for the duration of 1-h and return period of 2-y, the highest decrease is -17% for Sariyer station for the duration of 5-min and return period of 2-year. Rainfall intensities are decreasing in Olimpiyat station more than other stations for both RCPs. Findings of analyses are summarized in Table 4 for both RCPs. Table 4 contains average increases by percentage for each return period. When changes are considered from the point of return periods, average of percentage increase is the greatest for 2-y return period and it is the lowest for 100-y return period. This result reveals that, increase of rainfall intensities will be higher for shorter periods and lower for larger periods. But the same trend is not valid in terms of durations. Even though 24-h durations have the greatest average value of percentage increase, this value is not changing gradually, which means that rainfall intensities can increase more for shorter durations or longer durations. Analyses revealed that extreme rainfall intensities are increasing in the future with respect to historical (Figure 6 and Figure 7). Table 4 shows average percentage increase of IDF values under RCP4.5 and RCP8.5 scenarios with respect to historical IDF values in terms of return periods.

3.3 IDF Curve Trends of RCP4.5 and RCP8.5

As revealed in the previous section, rainfall intensities are increasing substantially under RCP4.5 and RCP8.5 scenarios. While rainfall intensities under RCP4.5 are increasing by an average of 30 to 45 percent for return periods, and 30 to 51 for durations, they are increasing by an average of 38 to 47 for return periods, and 38 to 57 for durations under RCP8.5. It is clear that RCP8.5 scenarios cause more extreme events with respect to RCP4.5 scenarios (Figure 8). In this section, the impacts of RCP scenarios on rainfall intensities are evaluated. Table 5 exhibits average of percentage increases of RCP8.5 with respect to RCP4.5 for each station, return period and duration. also shows IDF curve trends for both scenarios for a selected station. What stands out in Table 5 is RCP8.5 scenarios have higher rainfall intensities in all stations except Terkos station. In Terkos station, rainfall intensities are increasing for both scenarios with respect to historical IDF, but RCP4.5 has 6.59% higher rainfall intensities than RCP8.5 in terms of total rainfall intensities of return periods and durations. Olimpiyat is the station most affected by RCP8.5 with 14.5% difference to RCP4.5. In Florya station, RCP4.5 and RCP8.5 scenarios have almost the same trends for rainfall intensities. In total of all stations, RCP8.5 scenarios have 2.67% higher rainfall intensities. Rainfall intensities are increasing more for higher durations under RCP8.5, but increasing trend is almost same for all return periods. Table 5 demonstrates the total average percentage increase (when all return periods and durations are selected) of IDF values under RCP8.5 with respect to RCP4.5 for each station.

Table 6 shows the average total change of IDF values for RCP8.5 with respect to RCP4.5 only for each return period.

4. DISCUSSION

4.1 Applicability of the Disaggregation Model

The first analysis was performed using observed hourly rainfall data from Florya, Goztepe and Sariyer. Since the observed IDF curves for these stations were provided by the TSMS, they were used to verify the performance of the disaggregation method. Hourly rainfall data were disaggregated into sub-hourly data. Afterwards, IDF curves for disaggregated rainfall data were generated and compared to observed IDF curves. These comparisons revealed that there is a positive correlation between observed rainfall and disaggregated rainfall data by 2.8% total average change for three stations. Percentage differences between disaggregated and observed IDF curves were demonstrated in Table 1, Table 2, and Table 3. IDF curve trends for both disaggregated and observed IDF curves given in Figure 5 also show a close relationship between them. Therefore, the selected disaggregation method was applied to all data sets.

4.2 Behaviours of Rainfall Intensities in the Future

The second analysis can be considered the main analysis since it shows the differences between historical and future IDF curves. Hence, the impact of climate change can be observed with these comparisons. Historical and future IDF curves (for both RCP4.5 and RCP8.5) were generated for all stations. Afterwards, the generated IDF curves were plotted and compared. Conclusions of this analysis are listed as follows.

1. Most of rainfall intensities are increasing in terms of number of values for RCP4.5 and RCP8.5 rainfall intensities compared to historical rainfall intensities with a value of 95.4% (561 of 588 is increasing) and 98.30% (578 of 588 is increasing), respectively. Hence, rainfall events will be more intensified in the future compared to historical events and as a result, rainfall events will be more destructive.
2. Rainfall intensities will increase for shorter return periods more than higher ones. The evidence of this result implies that rainfall intensities will be higher for more frequent events in the coming future. For example, rainfall intensities are expected to rise by average 45% and 47% for 2-y return period, while percentages are 30% and 38% for 100-y return period, for RCP4.5 and RCP8.5, respectively.

3. There is no definite trend for increase in rainfall intensities in terms of durations, however 24-h rainfall intensities are expected to increase at a greater rate when compared to other durations for each RCP scenarios.

4. Minimum average percentage increase for RCP4.5 is 30% (in 100-y return period) and maximum one is 44% (in 2-y). The values are 38% (in 100-y) and 47% (in 2-y) for RCP8.5 compared to historical rainfall intensities.

5. Rate of increase in terms of total value of rainfall intensities under RCP4.5 is 36.5%, and under RCP8.5 is 42.3%. This result shows that rainfall intensities will be higher under RCP8.5 scenarios compared to RCP4.5.

6. For RCP4.5, the observed highest increase in terms of value of a specific rainfall intensity is 79.7% for Canta station for the duration of 24-h and a return period of 2-y. For RCP8.5, the highest increase is %74 for Omerli station for the duration of 1-h and return period of 2-y.

7. Most rainfall intensities increase for each duration and return period. However, rainfall intensities are decreasing in Olimpiyat station more than other stations for both RCPs.

8. Some rainfall intensities tend to decrease in the future. The highest decrease is -25% for RCP4.5 (Olimpiyat station for the duration of 2-h and a return period of 100-y). For RCP8.5, the highest decrease is -17% for Sariyer station for the duration of 5-min and return period of 2-year.

Briefly, the second analysis concludes that rainfall will be intensified in the future for both scenarios compared to historical events. Besides, it is possible to observe higher rainfall intensities for more frequent events compared to rare events in the coming future.

4.2 Which Climate Scenario is More Severe?

In the last analysis, differences between RCP4.5 and RCP8.5 scenarios were evaluated. As mentioned before, rainfall intensities tend to increase predominantly in the future compared to historical conditions. The results of this analysis are listed as follows:

1. While rainfall intensities under RCP4.5 are increasing by an average of 30 to 45 percent in terms of return periods, they are increasing by an average of 38 to 47 under RCP8.5. It is clear that RCP8.5 scenarios cause more extreme events with respect to RCP4.5 scenarios.

2. RCP8.5 scenarios have a higher rainfall intensity in all stations except Terkos station compared to RCP4.5. Rainfall intensities are higher by an average of 6.59% under RCP4.5 for Terkos. These results reflect those of (Xin, Zhang, Wu, & Fang, 2013; Pattnayak, Kar, Dalal, & Pattnayak, 2017; Camilo et al., 2018; Uraba, Gunawardhana, Al-Rawas, & Baawain, 2019; Vanli, Ustundag, Ahmad, Hernandez-Ochoa, & Hoogenboom, 2019) who also

concluded that RCP4.5 scenarios can have higher rainfall intensities for specific stations and seasons. The highest increase of rainfall intensities under RCP8.5 is 14.51% (for Olimpiyat station) compared to RCP4.5.

3. In total of all stations, RCP8.5 scenarios have 2.67% more rainfall intensities. Estimating higher rainfall intensities for RCP8.5 scenarios compared to RCP4.5 is expected according to the IPCC (2014). Rainfall intensities are increasing more for all return periods and durations under RCP8.5 more than that in RCP45 and this supports previous findings in the literature (Wang & Chen, 2014; Singh et al., 2016; Nilawar & Waikar, 2019). Rainfall intensities are increasing more for higher durations under RCP8.5, but increasing trend is almost same for all return periods. Rainfall intensities are increasing under RCP8.5 compared to RCP4.5 for all return periods, however the 100-y return period has the highest increase rate (2.84%). Briefly, RCP8.5 scenarios will give more extreme and destructive results in the future for most of the stations. When all stations are considered together, RCP8.5 scenarios have higher rainfall intensities for all return periods and durations.

5. CONCLUSIONS

The most serious cause of urban floods are short-duration heavy rainfall events. Therefore, the generation of IDF curves under all climate conditions requires the implication of short-duration rainfalls (from 5-min to 30-min). Besides, most of the current applications of IDF curves are stationary based, in other words, only historical rainfall events are evaluated to show possible upcoming events rather than considering climate change in the future. Therefore, generating updated IDF curves includes short-duration rainfalls considering both historical and future climate conditions was necessary. This study was performed to achieve the goal of generating updated IDF. Eight meteorological stations from Istanbul city were selected as study areas. RCP4.5 and RCP8.5 were preferred to obtain RCMs to represent future daily rainfall data. With a new approach to existing HYETOS method, future daily rainfalls were disaggregated by applying parameters of historical data for future rainfalls to be coherent with historical rainfall patterns. The study revealed that there is a close relationship between observed and disaggregated IDF curves. Therefore, the selected disaggregation method was applied to all data sets.

The results conclude that rainfall will be intensified in the future for both scenarios compared to historical events. Besides, it is possible to observe higher rainfall intensities for more frequent events compared to rare events in the coming future. RCP8.5 scenarios will give more extreme and destructive results in the future for all stations except Terkos. When all stations are evaluated as a whole, RCP8.5 scenarios have higher rainfall intensities compared to RCP4.5 for all return periods and durations.

The findings of this study support the idea that extreme events such as heavy rainfall will increase under climate change impacts in the future. On the other hand, the study revealed that selected disaggregation method HYETOS is a successful and reliable tool and it can be applied in hydrology studies.

This study once again demonstrated the need to use an updated IDF curve, which is generated under future climate conditions, for hydrology, hydraulic and other water related applications. Each RCM has its own characteristics and hence, future rainfall intensities can vary for each of them. Likewise, different disaggregation methods can simulate sub-hourly rainfall data in different ways. Therefore, future studies can be performed for more stations to enrich the awareness of climate change by evaluating more RCMs, disaggregation methods and distribution functions.

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DATA AVAILABILITY

The data that support the findings of this study are openly available at https://globalweather.tamu.edu , https://esgf-node.llnl.gov/search/esgf-llnl/ and after payment at https://mevbis.mgm.gov.tr/mevbis/ui/index.html#/Login

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TABLES

Table 1: Percentage differences between observed and disaggregated IDF curves for each duration and return period for Florya station.

Durations	Return Periods (Years)					
	2 y	5 y	10 y	25 y	50 y	100 y
5 min	1.17	2.44	1.67	-0.27	-1.97	-3.88
10 min	-0.94	1.91	3.03	3.59	3.72	3.60
15 min	-0.64	2.05	2.74	2.88	2.59	2.13
30 min	-2.08	1.14	3.01	5.05	6.36	7.56
1 h	-1.58	0.84	2.55	4.59	6.06	7.51
2 h	-1.96	-0.32	1.38	3.68	5.46	7.27
3 h	-3.35	-2.13	0.39	4.37	7.69	11.28
4 h	-3.20	-1.53	0.87	4.39	7.20	10.19
5 h	-3.88	-2.46	0.34	4.71	8.32	12.22
6 h	-4.19	-3.47	-0.52	4.56	9.04	13.93
8 h	-4.38	-4.37	-1.57	3.47	8.03	13.06
12 h	-4.80	-6.01	-3.11	2.72	8.21	14.52
18 h	-5.20	-7.81	-4.90	1.64	8.08	15.68
24 h	-4.99	-6.72	-3.98	1.94	7.68	14.41

Table 2: Percentage differences between observed and disaggregated IDF curves for each duration and return period for Goztepe station.

Durations	Return Periods (Years)					
	2 y	5 y	10 y	25 y	50 y	100 y
5 min	0.80	4.60	5.21	4.75	3.82	2.69
10 min	0.94	4.16	4.68	4.22	3.41	2.33
15 min	0.22	2.77	3.70	4.33	4.53	4.56
30 min	1.09	4.04	4.19	3.09	1.70	0.11
1 h	-1.82	-0.34	2.06	5.64	8.57	11.70
2 h	-0.53	0.22	1.58	3.63	5.28	7.03
3 h	-0.80	0.36	2.03	4.42	6.35	8.36
4 h	-0.75	0.00	1.55	3.91	5.83	7.85
5 h	-0.55	0.36	1.84	4.01	5.75	7.54
6 h	-0.21	1.00	2.29	3.99	5.24	6.46
8 h	-1.34	-0.30	1.62	4.66	7.15	9.89
12 h	-0.36	0.38	1.57	3.37	4.84	6.48
18 h	-0.09	0.43	1.24	2.50	3.56	4.78
24 h	0.01	0.92	1.06	1.00	0.91	0.82

Table 3: Percentage differences between observed and disaggregated IDF curves for each duration and return period for Sariyer station.

Durations	Return Periods (Years)					
	2 y	5 y	10 y	25 y	50 y	100 y
5 min	-0.18	1.48	1.42	0.85	0.19	-0.61
10 min	-0.92	1.46	2.24	2.65	2.69	2.64
15 min	-0.83	1.57	2.41	2.93	3.08	3.09
30 min	-1.70	2.48	4.33	5.81	6.51	6.91
1 h	-3.30	0.20	2.97	6.43	8.91	11.26
2 h	-1.56	0.98	2.97	5.52	7.40	9.26
3 h	-1.47	0.74	2.57	4.95	6.76	8.58
4 h	-1.47	0.68	2.69	5.42	7.56	9.79
5 h	-2.14	-0.16	2.32	5.98	8.92	12.09
6 h	-2.15	0.00	2.64	6.49	9.61	12.95
8 h	-1.50	-0.12	1.90	5.00	7.55	10.32
12 h	0.72	1.68	2.38	3.24	3.92	4.64
18 h	2.11	2.53	2.44	2.13	1.85	1.56
24 h	-5.08	-4.64	-2.75	0.53	3.49	6.78

Table 4: Average percentage increase of RCP4.5 and RCP8.5 IDF values compared to historical IDF values in terms of return period.

Scenarios	Return Period (Years)					
	2	5	10	25	50	100
RCP4.5	44.87	39.96	37.29	34.34	32.33	30.39
RCP8.5	47.18	44.66	43.06	41.09	39.64	38.15

Table 5: Total average percentage increase in IDF values under RCP8.5 compared to RCP4.5 for each station.

Olimpiyat	Sariyer	Sile	Goztepe	Florya	Terkos
14.51	3.025	2.49	2.48	0.11	-6.59

Table 6: Total average change in IDF values under RCP8.5 compared to RCP4.5 in terms of return periods.

Return Period (Year)	2	5	10	25	50	100
Average Change (%)	2.60	2.51	2.59	2.70	2.78	2.84

FIGURE LEGENDS

Figure 1: Location of Istanbul city.

Figure 2: Eight meteorological stations selected as study areas.

Figure 3: Used data types including historical 1-minute and hourly rainfalls (mm) from the Turkish State Meteorological Service (TSMS), historical simulated daily rainfall from the Regional Climate Model (RCM), historical daily rainfall from the Climate Forecast System Reanalysis, future daily rainfalls generated under Representative Concentration Pathways (RCP) 4.5 and 8.5 scenarios from the RCM, and historical IDF curves generated with observed rainfalls from the TSMS.

Figure 4: Framework of bias-correction process developed by Rathjens et al. (2016).

Figure 5: Plottings of IDF curves generated with observed and disaggregated rainfalls for Sariyer, Florya, and Goztepe stations to show the performance of the disaggregation model.

Figure 6: RCP4.5 and RCP 8.5 future IDF curve trends compared to historical IDF curves for stations Olimpiyat, Goztepe and Florya stations.

Figure 7: RCP4.5 and RCP 8.5 future IDF curve trends compared to historical IDF curves for stations Terkos, Sile, and Sariyer stations.

Figure 8: Comparison of IDF curve trends under RCP4.5 and RCP8.5 scenarios for stations Sile, Terkos, Olimpiyat, Sariyer, Florya, and Goztepe stations.