

HYDROLOGICAL MODELING USING HIGH SPATIO-TEMPORAL
RESOLUTION CLIMATE DATA :
A CASE STUDY FOR BOZKURT, KASTAMONU

by
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Finally, I dedicate this work to all communities and ecosystems vulnerable to the impacts of climate change, with the hope that science continues to support resilience, preparedness, and protection. This thesis is a small step toward that purpose.

ABSTRACT

HYDROLOGICAL MODELING USING HIGH SPATIO-TEMPORAL RESOLUTION CLIMATE DATA : A CASE STUDY FOR BOZKURT, KASTAMONU

This thesis integrates convection-permitting climate modeling with catchment-scale hydrological simulation to analyze the 2021 flash flood in Bozkurt, Kastamonu, and assess future flood risk under climate change. High-resolution precipitation and temperature data were produced using RegCM5 with a non-hydrostatic core, and used to drive the SWAT model in the Ezine Stream basin. Flash floods, triggered by short-duration intense rainfall and steep terrain, are among the most destructive hydrometeorological hazards. Bozkurt was selected due to its topography and vulnerability, with the August 2021 flood used as the reference event. The study aims to (1) simulate the 2021 flood, (2) evaluate runoff and streamflow under current and future conditions, and (3) assess flash flood potential.

Results show that RegCM5–MOLOCH can capture convective rainfall patterns when configured with high resolution and proper domain setup, though some timing and spatial shifts occurred. SWAT was useful for general runoff trends but limited in flash flood timing. Future projections indicate an increase in short, intense rainfall events. The integrated modeling approach contributes to understanding local flood risks and supports future preparedness.

Keywords: RegCM5, convection-permitting modeling, non-hydrostatic core, SWAT, flash floods, climate change, hydrological modeling, Bozkurt

ÖZET

YÜKSEK UZAMSAL-ZAMANSAL ÇÖZÜNÜRLÜKLÜ İKLİM VERİSİ İLE HİDROLOJİK MODELLEME : BOZKURT (KASTAMONU)

Bu tezde, konveksiyon çözümlü iklim modeli çıktıları ile havza ölçekli hidrolojik modelleme birleştirilerek Bozkurt (Kastamonu)'da meydana gelen 2021 seli simüle edilmiş ve iklim değişikliği altında gelecekteki risk değerlendirilmiştir. Çalışmada, yüksek çözünürlüklü ve non-hidrostatik çekirdekli RegCM5 modeli kullanılarak yağış ve sıcaklık verileri üretilmiş; bu veriler, Ezine Deresi havzasında yüzey akışı ve akım dinamiklerini incelemek amacıyla SWAT modeline entegre edilmiştir.

Ani seller, kısa süreli ve şiddetli yağışlarla oluşan, özellikle dik topoğrafyada etkili olan yıkıcı olaylardır. Bozkurt bölgesi, dar vadileri ve artan kırılganlığı nedeniyle örnek alan olarak seçilmiştir. Çalışma üç temel amacı hedeflemektedir: (1) 2021 selinin simülasyonu, (2) mevcut ve gelecekteki koşullarda akış analizleri, (3) bölgenin ani sel potansiyelinin değerlendirilmesi.

Sonuçlara göre, RegCM5–MOLOCH modeli yüksek çözünürlük ve uygun domain yerleşimi sağlandığında konvektif yağışı başarıyla yakalayabilmektedir; ancak bazı senaryolarda zamanlama ve konum kaymaları gözlenmiştir. SWAT modeli genel akış eğilimlerini vermekte yeterli olmuş, ancak ani seli zamanında yakalamakta sınırlı kalmıştır. Gelecek projeksiyonları, kısa süreli şiddetli yağışlarda artışa işaret etmektedir. Bu bütünleşik modelleme yaklaşımı, yerel taşkın risklerinin anlaşılmasına katkı sağlamaktadır.

Anahtar Kelimeler: RegCM5, konveksiyon çözümlü modelleme, non-hidrostatik çekirdek, SWAT, ani seller, iklim değişikliği, hidrolojik modelleme, Bozkurt

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LIST OF ACRONYMS/ABBREVIATIONS

CEC	Cation Exchange Capacity
CLM	Community Land Model
CP-RCM	Convection-Permitting Regional Climate Model
DEM	Digital Elevation Model
ECMWF	European Centre for Medium-Range Weather Forecasts
ERA5	ECMWF Reanalysis version 5
FF	Flash Flood
FFPI	Flash Flood Potential Index
FFVI	Flash Flood Vulnerability Index
GHG	Greenhouse Gas
GIS	Geographic Information System
HRU	Hydrologic Response Unit
IPCC	Intergovernmental Panel on Climate Change
LST	Land Surface Temperature
LU/LC	Land Use / Land Cover
LULC	Land Use Land Cover
MAE	Mean Absolute Error
NSE	Nash–Sutcliffe Efficiency
PBL	Planetary Boundary Layer
RCM	Regional Climate Model
RegCM5	Regional Climate Model version 5
RMSE	Root Mean Square Error
SoVI	Social Vulnerability Index
SRTM	Shuttle Radar Topography Mission
SWAT	Soil and Water Assessment Tool
USGS	United States Geological Survey
WGS84	World Geodetic System 1984

1. INTRODUCTION

Floods are defined as an overflow of water at or near the point where the rain fell onto. The type of the flood can be changed, but the impact is mostly the same; floods can threaten lives, damage properties and businesses, prevent access to public services, cause evacuation and forced displacement.

According to the World Meteorological Organization (WMO) reports, floods accounted for 44% of all disasters and 31% of total economic losses between 1970 and 2019[1]. The increase in flood damage is not solely due to the effects of climate change; urbanisation and population growth are also significant contributing factors [2]. The impact of the floods also changed according to the level of economic development of the region, and like many other effects of climate change, the damage of floods is also unevenly distributed. Between 1994 and 2013, floods affected nearly 2.5 billion worldwide. Floods cause more than \$40 billion in damage each year around the world [3].

The effects of floods are not constraining only people's lives or economic losses; floods also cause psychological consequences. The studies examined clearly indicate that flooding is a significant source of stress, with its ramifications felt long after the water levels have returned to normal. Flooding impacts individuals of all ages and can lead to various consequences, including bereavement, economic difficulties for families, behavioural issues in children, heightened substance use or misuse, increased domestic violence, and the exacerbation or triggering of existing mental health problems [4].

Floods can be classified based on their source—each posing unique challenges in terms of forecasting, impact assessment, and mitigation strategies. There are three main types such as; fluvial floods, pluvial floods, and coastal floods [5]. The definition provided by the Republic of Türkiye Ministry of Forestry and Water Affairs' Turkish State Meteorological Service aligns closely with this approach.

The impact of the hazard and the actions to enhance resilience will vary depending on the type of flood. Therefore, understanding the type of flood in the study area is crucial for finding the appropriate application of the hydrologic model and data selection and subsequently measuring the effect of future floods, preparing hazards, and developing resilience.

Fluvial floods can be defined as rising water levels in a river, lake, or stream and damaged neighbouring lands. The cause of this type of flood is mostly excessive rain or snowmelt. The Turkish State Meteorological Service specifies the time of the fluvial floods; they occur in springtime. This type of flood is widespread in Europe, Mediterranean countries, and Türkiye. The floods in Antalya and Mersin (2016 - Turkey), Aude Region (2018 - France), Veneto Region (2020 - Italy), Mediterranean Strom Ianos (2020 - Greece) and Western Europe (2021 - Germany, Belgium, and the Netherlands) are the recent and severely damaging examples of fluvial floods.

Coastal floods are commonly known as storm surges; for this type of flood, land along the coast is needed. The floods that occurred because of tsunamis are an example of this type. Due to geographic location of Türkiye, coastal floods are defined by the Turkish State Meteorological Service (MGM) as primarily caused by volcanic activity or storms, leading to sea overflow. The floods in Catania (2021 - Italy), Athens (2021 - Greece), Marseille (2021 - France), L'Aquila (2021 - Italy), Venice (2020 - Italy), and Izmir (2020 - Türkiye) are the recent examples of coastal floods.

Pluvial floods' main reason is extreme rainfall events; contrary to commonly held beliefs, this type of flood does not need a waterbody nearby. It can occur at any location at any time. The floods in Madrid (2021 - Spain), Toulouse (2018 - France), Athens (2020 - Greece), Sicily (2021 - Italy), Cyprus (2022) and Istanbul (2023 - Türkiye) are recent cases of pluvial floods. Flash floods are also a subtype of pluvial floods, defined as a flood caused by heavy or excessive rainfall in a short period of time (generally less than six hours) within the vicinity or on nearby elevated terrain. The areas that experienced wildfires recently are vulnerable to flash floods. The floods in

Bordeaux (2019 - France), Athens (2017 - Greece), Catania (2021 - Italy) and Bozkurt (2021 - Kastamonu, Türkiye) are examples of flash floods. The recent event in Texas was a huge flash flood event which caused 121 people's death and approximately 161 people missing. The flood occurred within 4-hour intense rainfall.

To better understand flood dynamics and distribution, EM-DAT data can be used. In the Figure 1.1, Figure 1.2 and Figure 1.3, EM-DAT disaster data for flood examined according to flood type; Figure 1.7, Figure 1.8 and Figure 1.9 shows flood severity indexes as a box plot. Histogram of the flood severity index can be found in Figure 1.4, Figure 1.5 and Figure 1.6. Also total loss and death analysis performed, in the Figure 1.10, Figure 1.11 and Figure 1.12 visualization of the analysis can be found.

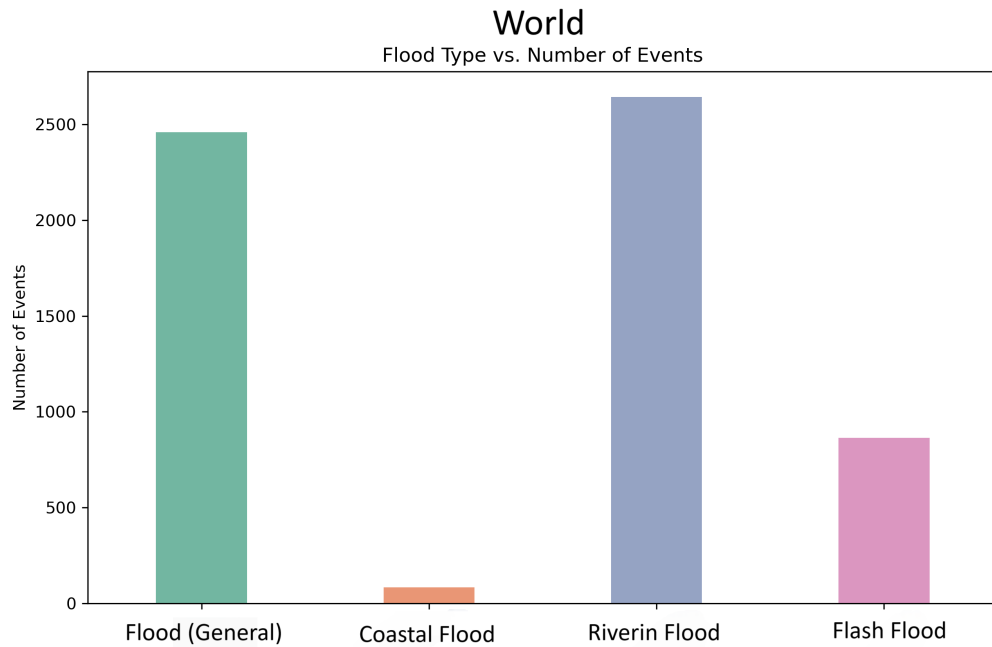


Figure 1.1. Flood Type Distribution - World.

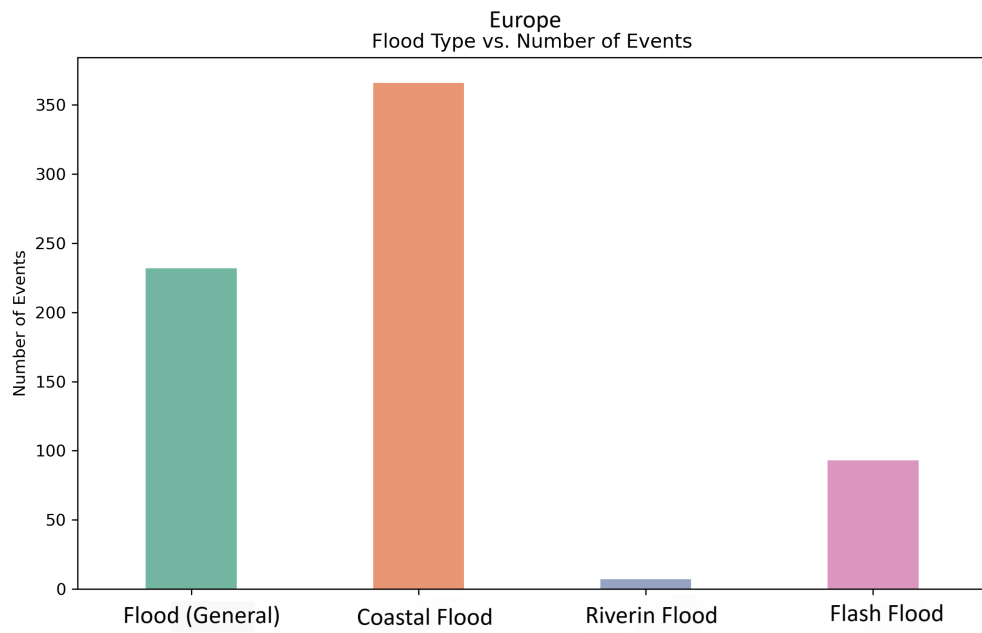


Figure 1.2. Flood Type Distribution - Europe.

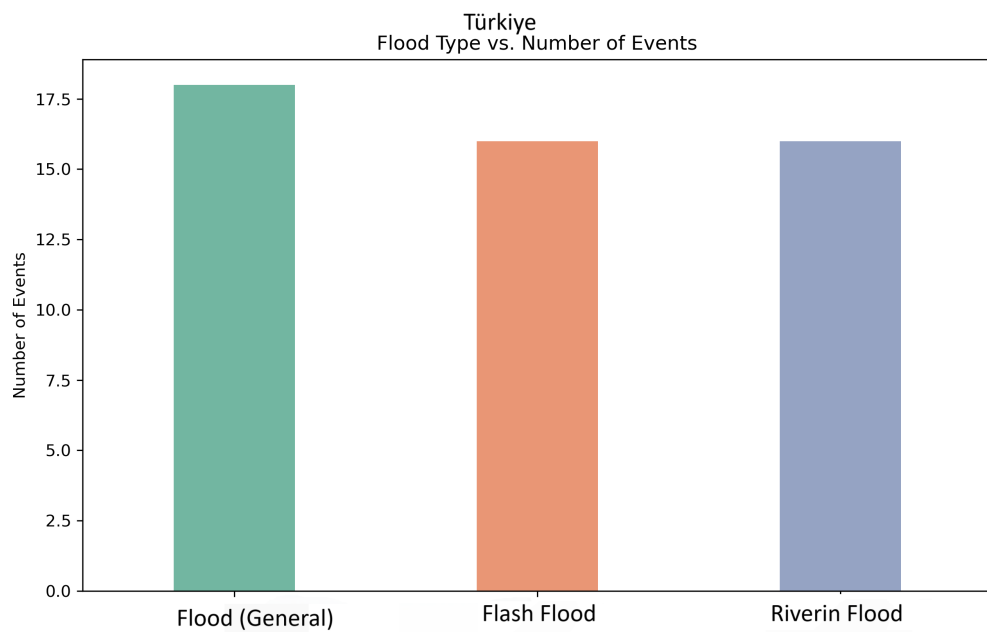


Figure 1.3. Flood Type Distribution - Türkiye.

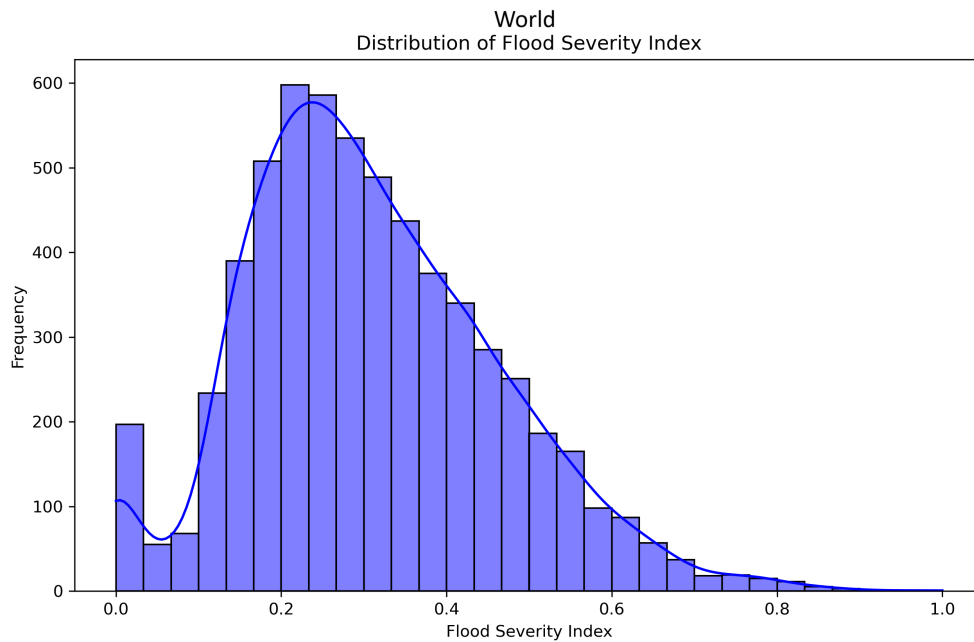


Figure 1.4. Distribution of Flood Severity Index - World.

As you can see in the graphs most of the flood events labeled as general flood without any specialization, riverine flood is the highest type of flood for, in total, Europe and Turkey. In Turkey, there is no coastal flood since it has no ocean shore. However, flash floods represent much of Turkey's flood. Flash floods and associated flood disasters are common in Turkey. According to national disaster databases, there have been more than 1,000 flood events in the last few decades. For instance, between 1960 and 2014, 1,076 flood incidents were recorded by the Turkish Disaster Database (TABB), resulting in 795 fatalities and approximately US \$800 million in damages. A significant portion of Turkey's natural disasters are floods; in fact, floods account for almost 30% of all natural disasters that have been documented in the country. Flood occurrences have been generally increasing since the mid-1990s, although temporal trends indicate significant variability from year to year. The increasing risk is further highlighted by recent climate statistics, which show that in 2021 alone, Türkiye experienced 107 flood events, which was significantly more common than other disaster types like landslides or wildfires. Türkiye is unquestionably one of the most flood-prone nations in its region due to the high frequency of flash floods [6].

Flood Severity Index (FSI) data at the national (Türkiye), continental (Europe), and global scales were used to analyze the spatial patterns of flood severity using box plots and histograms. The majority of flood events worldwide are concentrated in the low to moderate severity range (0.2 - 0.4), while a small number of extremely severe events push the upper tail above 0.8. This indicates that the distribution of FSI is right-skewed. All flood types—general, coastal, riverine, and flash—share comparable median severities, according to box plots; however, there are more high-severity outliers in riverine and general floods. A similar pattern is seen in Europe, although there are fewer extreme outliers and a somewhat smaller overall spread.

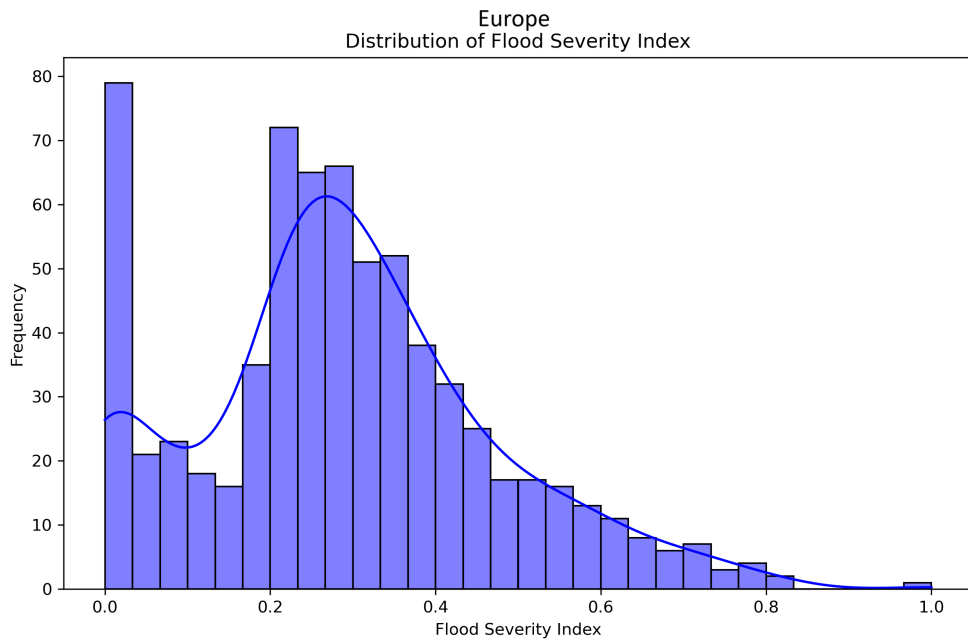


Figure 1.5. Distribution of Flood Severity Index - Europe.

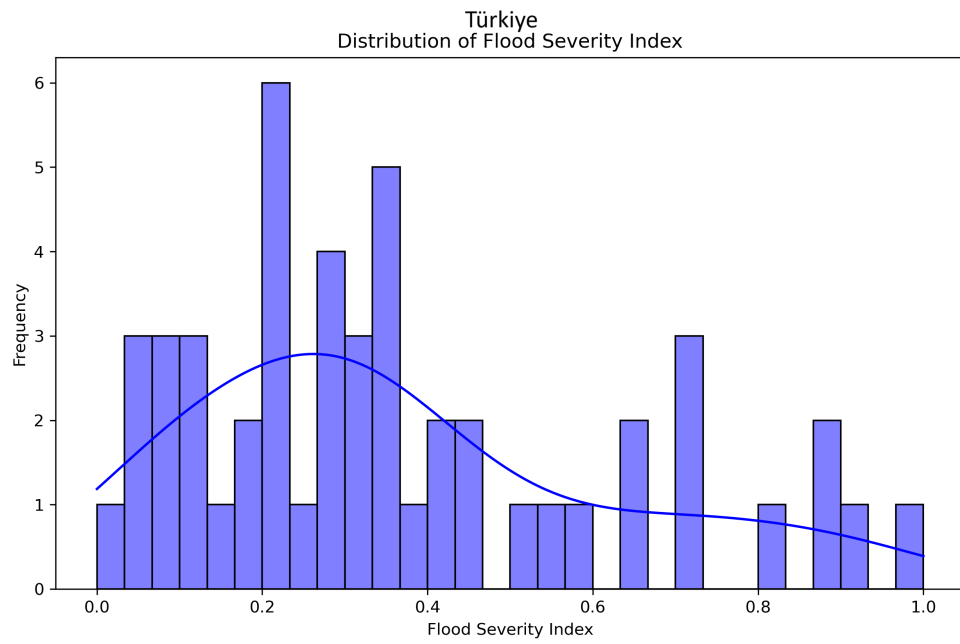


Figure 1.6. Distribution of Flood Severity Index - Türkiye.

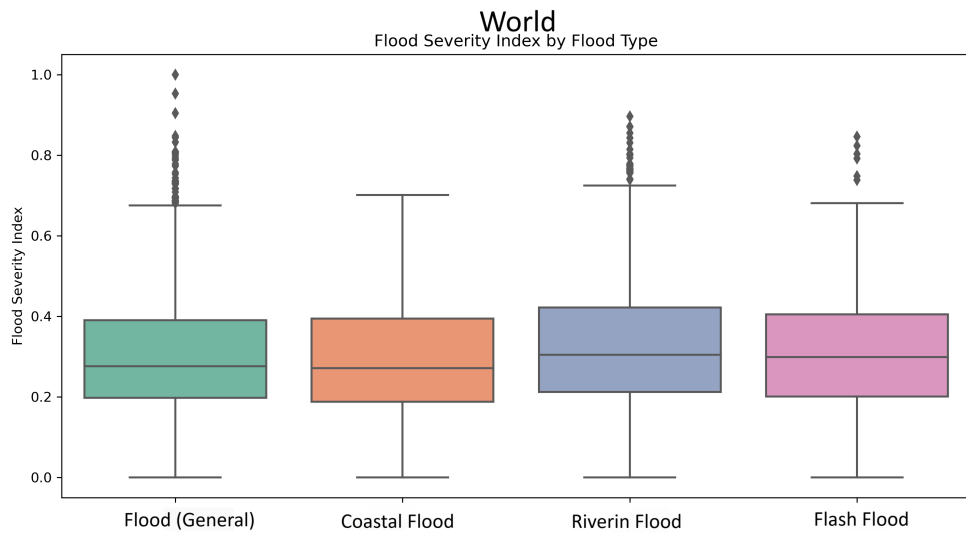


Figure 1.7. Flood Severity Index by Flood Type - World.

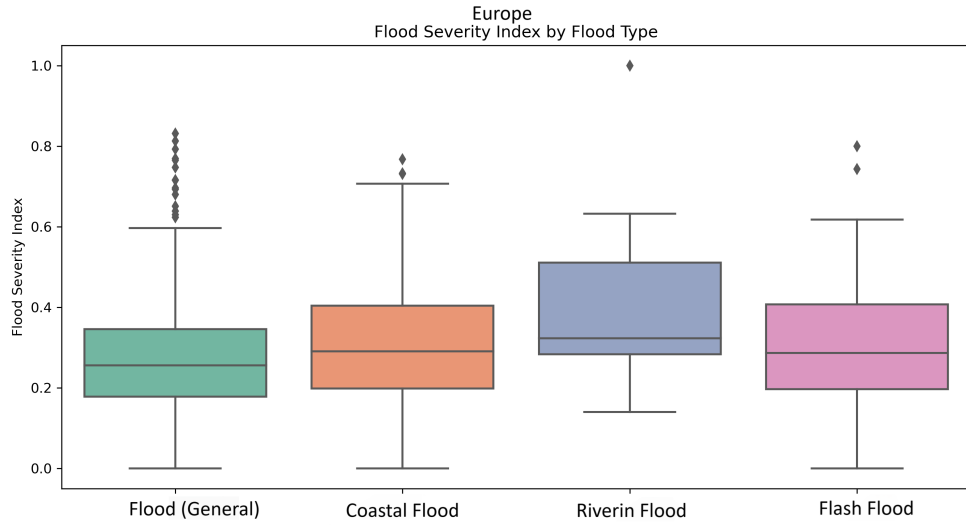


Figure 1.8. Flood Severity Index by Flood Type - Europe.

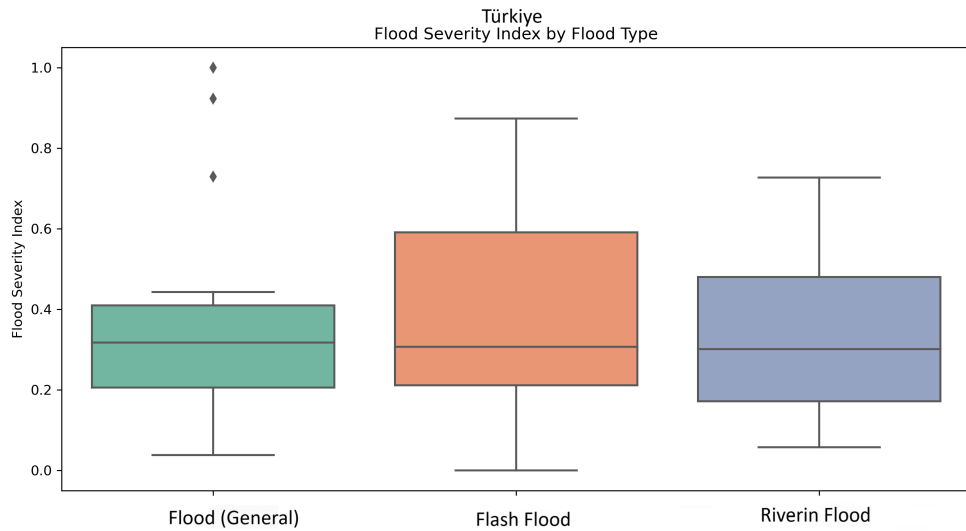


Figure 1.9. Flood Severity Index by Flood Type - Türkiye.

In comparison to the global data, the median severity of coastal floods in Europe is higher, and the histogram shows a denser clustering around the 0.2–0.3 range, suggesting fewer high-severity events. The situation in Türkiye, on the other hand, is different: the box plots show that flash floods have significantly greater variability and outlier severity than other types, with some instances coming close to the maximum FSI. With multiple high-severity events (above 0.6) and a flatter, more irregular shape,

the Turkish histogram is likewise skewed to the right, indicating that extreme flood events happen more frequently than in Europe. This comparison demonstrates how topography and regional features affect flood dynamics, highlighting the necessity of context-specific risk assessments and policy interventions, particularly in nations like Türkiye that are vulnerable to flash floods.

A spatially differentiated view of flood impacts at the global, European, and Turkish scales is offered by the scatter plots of total deaths versus total affected individuals from flood events. The scatter plot shows a wide range of impacts at the global level, with some extreme outliers, especially one riverine flood that killed over 3.5 million people and others that affected over 200 million. High-impact bubbles are dispersed throughout all flood categories, and the flood types and magnitudes of these worldwide occurrences vary greatly. The scope is more limited in Europe, where the majority of incidents impact fewer than 1.5 million people and deaths seldom surpass 2,000.

The high-impact zone is dominated by general and coastal floods, whereas flash floods are common but typically have smaller bubble sizes (i.e., lower impact index). The Turkish flood data, on the other hand, indicates more moderate overall figures, with affected populations of less than 1.2 million and total deaths per event typically falling below 200. However, a few relatively high-impact flash and general floods with noticeably large bubble sizes are highlighted in Turkey's scatter plot, suggesting disproportionate damage in relation to population size or event frequency. Turkey's flood profile is more condensed than the global and European patterns, but it still contains occurrences with significant repercussions. These trends highlight the significance of regional context in disaster management: localized events in Turkey and Europe can still have high per-event costs, even though global floods show enormous scale and variability.

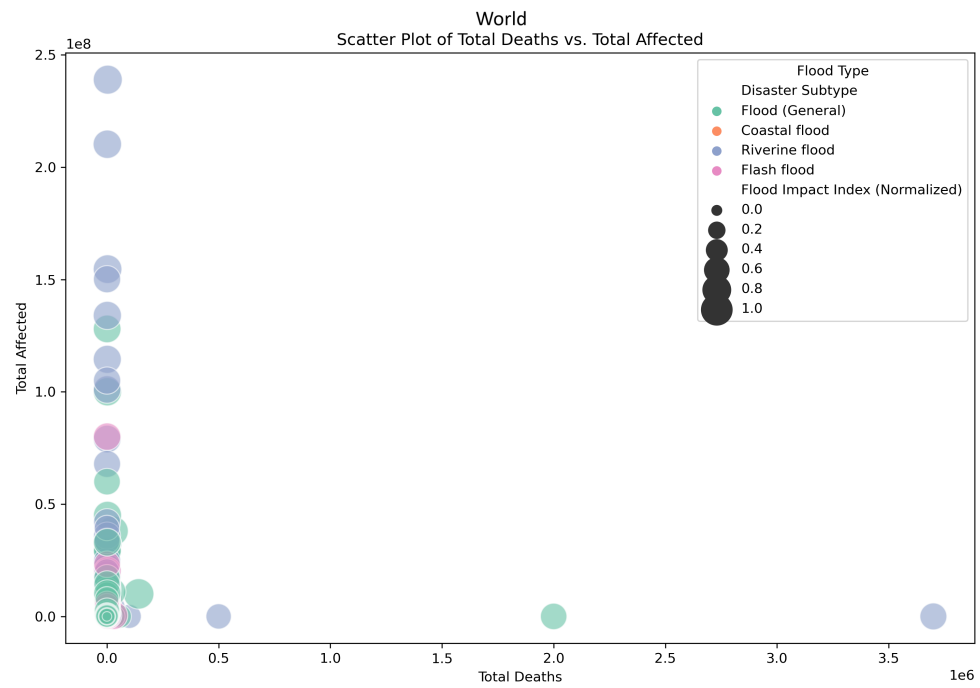


Figure 1.10. Comparison of Total Deaths versus Total Effected - World.

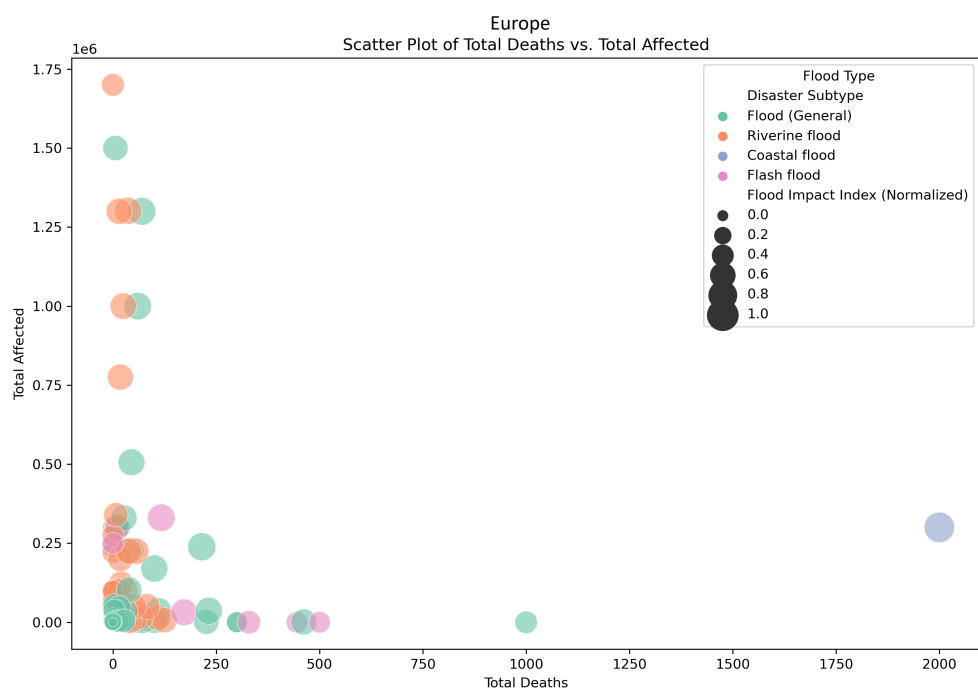
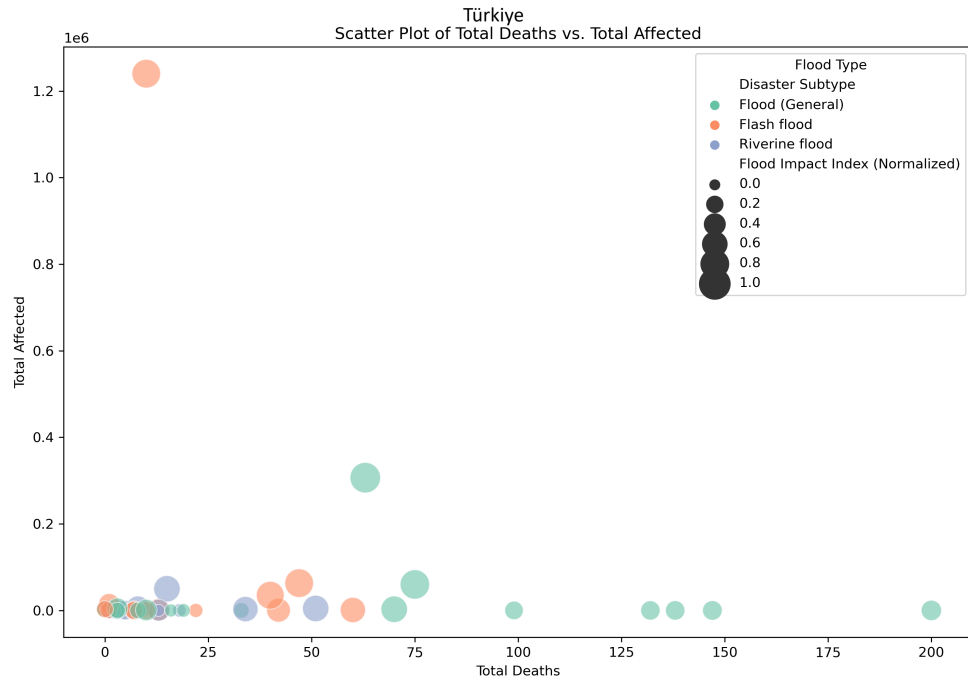


Figure 1.11. Comparison of Total Deaths versus Total Effected - Europe.



overflowing waterways. In many provinces, the Turkish State Meteorological Service has recorded increasingly irregular rainfall, highlighting the susceptibility of both heavily populated cities and rural basins to unexpected flooding. While different regions have different flood-generating mechanisms (rainfall vs. snowmelt), flash floods generally occur most frequently in coastal provinces of Türkiye and urbanized floodplains [7].

Capturing the main drivers of flooding is the main perspective of future prediction of flooding. In the literature there are five main drivers such as: rainfall intensity and duration, snowmelt contribution, sea level rise, storm surge height and temperature trends [8]. Due to the significance of understanding flood dynamics, numerous studies have focused on detecting the frequency, size, and characteristics of floods. Measuring the impact of flood depends on the objective of the study. Hydrological metrics are widely used characteristics of the impact studies. Hydrological metrics include flood depth, flood duration, flood extent, flood velocity, peak discharge of the flood event and return period [9]. Resilience and recovery metrics are mostly used for adaptation research. This metric includes recovery time, community resilience index (CRI), disaster preparedness levels and social capital [10]. Most insurance based research used social, economic and infrastructure metrics. They include affected population, casualties, evacuation numbers, accessibility loss, direct/indirect economic loss, cost of emergency services, economic vulnerability index and reconstruction costs [11]. The other metric can be defined as environmental metrics, this metric evaluates the impact of floods on ecosystems. Environmental metrics include wetland expansion, erosion and sedimentation, water quality, biodiversity impact [10].

To better identify regions vulnerable to such events, various composite indicators have been proposed to integrate multiple environmental variables into a single risk metric. Flood vulnerability index combines physical vulnerability, socioeconomic factors, and hazard exposure) to assess the overall vulnerability of a region to floods. It is useful for flood mitigation research [12]. The Flood Resilience Index (FRI) is a combined index that evaluates the resilience of communities to flood events by considering infras-

structure, social capacity, and policy interventions[13]. The Risk to Resilience (R2R) index assesses the transition from risk exposure to the community’s ability to recover and adapt [14]. The Human Exposure and Vulnerability Index (HEVI) index focuses on combining demographic and environmental factors to assess human exposure and vulnerability to floods [15].

Flash floods are rapid-onset events, typically occurring within six hours of intense rainfall, and are shaped by complex interactions between meteorological, hydrological, and geomorphological processes. Therefore, indexes for flash floods vary in the literature. Soil Moisture Index (SMI): Indicates how close the soil is to saturation. Derived from satellite observations or modeled data, SMI is often used to define pre-event conditions for flood modeling [16]. Flash Flood Guidance (FFG): Developed by hydrometeorological services, FFG provides the amount of rainfall over a given period needed to trigger flooding. It is based on real-time soil moisture and antecedent rainfall. Storm Severity Index (SSI): Combines rainfall intensity and storm duration with local terrain features to estimate the impact potential of a given convective event [17]. Compound Flood Risk Index: Incorporates multiple overlapping risks such as pluvial (rainfall), fluvial (river overflow), and urban flood hazards. Useful for basin-scale assessments where multiple sources of flooding can interact. Among them, the Flash Flood Potential Index (FFPI) is one of the most commonly applied tools in both operational forecasting and academic studies [18][19].

According to the IPCC’s AR6 report, an increase in the extreme precipitation led to an increase in the frequency and magnitude of especially fluvial floods. Estimates of flood exposure using satellite-derived inundation area and high-resolution population data showed a 20–24% increase during 2000–2018 [20]. Over the past 40-60 years, rising temperatures have caused spring floods to occur approximately 10 days earlier, depending on the location. There is a complex relationship between extreme rainfall and future pluvial floods. While some regions are experiencing an increase in extreme precipitation, resulting in a higher frequency of pluvial and fluvial floods, other areas are witnessing a decreasing trend due to various contributing factors such as soil

wetness, land cover change, water usage within the river basin or cryospheric change. Unfortunately, there is a knowledge gap regarding ice-related floods, particularly those associated with glacial lake studies [21]. In Türkiye, the presence of glacial lakes such as Lake Van, Çıldır Lake, Karagöl; presents an opportunity for future research on their potential relationship with flash floods; however, this area remains underexplored for now.

The flash flood event in Kastamonu, Bozkurt region is the baseline event for this research. The climate and cartography of the region are convenient for a flash flood event. The flood resulted in at least 38 fatalities, at least 80 injuries, and the evacuation of 2,000 residents from the region. Approximately 1,000 buildings and 100 vehicles were damaged; the agricultural effect of the flood was not calculated, but according to reports, there was extensive destruction of the crops [22].

Within the scope of our research, we will specifically examine studies that utilise the SWAT and RegCM models. The latest research on flood prediction primarily focuses on three main approaches: the use of GIS tools (such as ArcGIS and QGIS) with hydrological modelling tools (such as SWAT) [23], different machine learning techniques (such as artificial neural networks) [24], and more combined approaches which are using a mix of two techniques simply AI powered GIS [25]. Studies can also be categorised according to their primary focus, as floods impact various sectors differently—including the environment [26], economy [27], society [27], public health [29], agriculture [30], and transportation [31]. The primary focus area determines the metrics used for comparison and influences the prediction data required.

Flash flood prediction is a critical area of research, particularly in regions prone to rapid hydrological changes. The integration of Regional Climate Models (RCMs) and the Soil and Water Assessment Tool (SWAT) has emerged as a promising approach to enhance the accuracy of flash flood forecasts. RCMs utilize high-resolution climate data to simulate localized weather patterns, which are essential for understanding precipitation dynamics that lead to flash floods [32]. These models can capture the intricate

interactions between atmospheric conditions and land surface processes, providing valuable insights into potential flood events. Climate models can assist in predicting future climate variables, such as temperature, precipitation, and wind. The causes of floods can be simply explained as excess rainfall in a given area; therefore, climate models are valuable tools for predicting future flood events, estimating flood return periods, and assessing flood probabilities. RegCM and the new capabilities of the fifth version, especially convective-permitting, allow it to predict future flood events for smaller areas [33]. The main idea is simulating the weather conditions of the selected important flood event, and in the future predictions of the precipitation, the flood-caused rain pattern will be trying to catch.

The SWAT model complements RCMs by simulating the hydrological response of watersheds to various climatic inputs. It allows for the assessment of how land use, soil characteristics, and topography influence runoff and infiltration processes, which are critical for flash flood occurrence [34]. For instance, the application of SWAT in conjunction with RCM outputs can help in developing inundation hazard maps, as demonstrated by Saber et al., who utilized a rainfall-runoff-inundation model to map flash flood vulnerabilities in Egypt [34].

This integrated approach not only enhances predictive capability but also aids in identifying high-risk areas for targeted intervention. The other drivers of floods can simply be summaries as topographic properties of the area, land use and soil properties. GIS tools can help us to understand the flood drivers in a nutshell, therefore they are effective and preferred approaches for flood predictions. Different types of hydrostatical models are available such as; Soil and Water Assessment Tool (SWAT), Hydrologic Engineering Center - Hydrologic Modeling System (HEC-HMS), Cold Regions Hydrological Model (CRHM). All models have their advantages in different areas and methodologies. In the literature SWAT is preferred because of its user-friendly interface, widely usage and large community, open source and includes pre-built datasets and tools, including NASA's TRMM precipitation data, MODIS land cover data. In the flood research SWAT is widely used, this feature will allow us to validate our results

with the different other researchers' results.

The combination of CP-RCM and SWAT provides a robust framework for hydrological modeling, allowing for the simulation of rainfall-runoff processes essential for flash flood prediction. RCMs can generate high-resolution climate data, which, when coupled with SWAT's capabilities to model watershed processes, can yield detailed predictions of hydrological responses to precipitation events. For instance, studies have demonstrated that integrating RCM outputs with SWAT can effectively simulate streamflow and identify potential flash flood occurrences in various regions, including arid and semi-arid areas [35][36]. The performance of these models is often evaluated using statistical measures such as the Nash-Sutcliffe Efficiency (NSE) and the coefficient of determination (R^2), which provide insights into the models' predictive accuracy[36][37].

Moreover, advancements in machine learning techniques, as highlighted by Alamoudi, have shown promise in improving flash flood susceptibility predictions when combined with hydrological models like SWAT. Machine learning and artificial intelligence techniques have been widely used for climate change research recently. Different approaches are available, but the main idea of machine learning-powered climate change research is using the different and a lot of data. Today we have a significant amount of data about climate change, among others, historical climate data and extremes data, remote sense data, satellite data, and climate model data. Machine learning, especially neural networks, can help to predict future trends by using historical data or understanding flood patterns and predict damage of a possible event by using remote sensing and satellite. Machine learning algorithms can analyze vast datasets to identify patterns and correlations that traditional models might overlook [36].

Machine Learning techniques further enhance flash flood prediction by leveraging large datasets, including meteorological and hydrological variables. Various ML models, such as Support Vector Machines (SVM), Random Forest (RF), and Neural Networks, have been employed to assess flash flood susceptibility and predict occur-

rences based on historical data. The effectiveness of these models is frequently quantified using Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) metrics, which allow for a comparative analysis of model performance [38][39]. For example, the AUC metric provides a clear representation of a model's ability to distinguish between flood and non-flood conditions, with higher values indicating better predictive capability [39][40]. The use of Support Vector Machines (SVMs) in predicting flash floods has been shown to significantly enhance prediction accuracy by incorporating variables such as precipitable water vapor and surface pressure [38]. This synergy between machine learning and hydrological modeling represents a significant advancement in flash flood forecasting methodologies. In the mixed approaches, machine learning can be used for predicting missing data, examining outputs of GIS tools or climate models, but mostly the approaches are using decreasing computational costs or finding more effective ways for the predictions.

The importance of real-time data integration cannot be overstated. Early warning systems, such as those discussed by Alasali et al., leverage real-time monitoring and predictive modeling to provide timely alerts about potential flash flood events [41]. These systems utilize a combination of remote sensing data and hydrological models to deliver accurate forecasts, thereby enabling effective disaster management strategies. The integration of such systems with RCM and SWAT models can further enhance their predictive capabilities, ensuring that communities are better prepared for flash floods.

In terms of result representation, the Flash Flood Potential Index (FFPI) has emerged as a valuable tool for visualizing flash flood susceptibility across regions. This index is derived from multi-criteria decision-making processes that incorporate various hydrological and geomorphological factors, allowing for a comprehensive assessment of flood risk [42][43]. Additionally, probabilistic forecasting methods have been developed to provide a more nuanced understanding of flash flood risks, taking into account uncertainties in precipitation estimates and hydrological responses [44][45].

In conclusion, the combination of RCMs and SWAT, augmented by machine learning techniques and real-time monitoring systems, provides a robust framework for flash flood prediction. This integrated approach not only improves the accuracy of forecasts but also enhances the capacity for effective risk management and mitigation strategies in vulnerable regions. The comparative indices and result representations employed in these methodologies, such as AUC and FFPI, facilitate a better understanding of flood risks and enhance the accuracy of predictions, ultimately contributing to improved disaster management strategies.

Based on this information, this research focuses on Bozkurt, Kastamonu, a small study area, with the primary aim of predicting future flash flood trends using the SWAT model with precipitation outputs from the fifth version of the Regional Climate Model (RegCM5) in a non-hydrostatic, convection-permitting configuration. Our approach will begin by simulating the Bozkurt flood event using ERA5 data. Once this initial simulation is validated, we will proceed to examine future flood predictions for the region. A detailed methodology will be provided in the Study Design section.

2. MATERIALS AND METHOD

2.1. Domain

2.1.1. Study Area

This study focuses on the Bozkurt district of Kastamonu, located in the Western Black Sea Region of Türkiye. Bozkurt lies in a steep and narrow valley formed by the Küre Mountains, with the town center positioned around 41.95°N, 34.00°E. The average elevation of the town is approximately 100 meters, but the surrounding terrain rises sharply, reaching over 1000 meters in places. (Figure 2.1 and Figure 2.2)

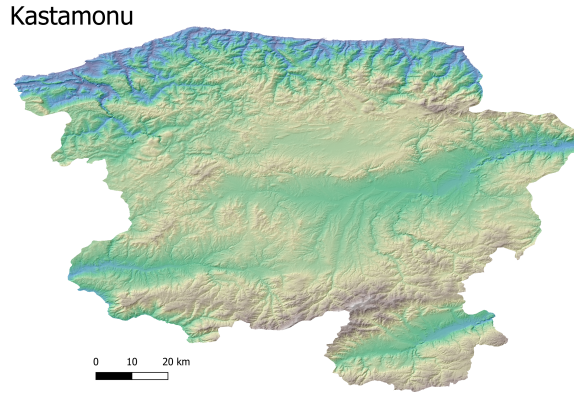


Figure 2.1. Geography of Kastamonu.

The settlement is small, with fewer than 10,000 residents, and most buildings and infrastructure are located along the riverbanks. Due to the narrow valley floor and steep topography, Bozkurt is particularly vulnerable to flash floods. This geographic setting makes it an ideal case study for evaluating flood risk using climate-hydrology modeling tools like RegCM5 and SWAT.

Bozkurt

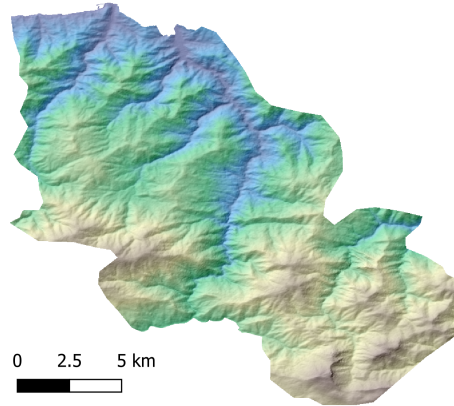


Figure 2.2. Geography of Bozkurt.

2.1.2. Hydrological Characteristics

The area is primarily drained by two streams: Ezine and İlişi. The Ezine stream is the dominant one and flows directly through Bozkurt's urban center. It collects runoff from the mountainous areas and discharges into the Black Sea. The Ezine stream catchment area is approximately 70–80 km² [46]. The İlişi stream is smaller but still contributes to surface flow, especially during intense rainfall events. (Figure 2.3 and Figure 2.4)

Kastamonu - Rivers

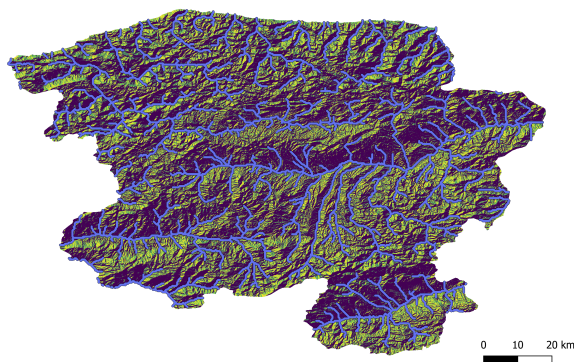


Figure 2.3. Rivers of Kastamonu.

Bozkurt - Rivers

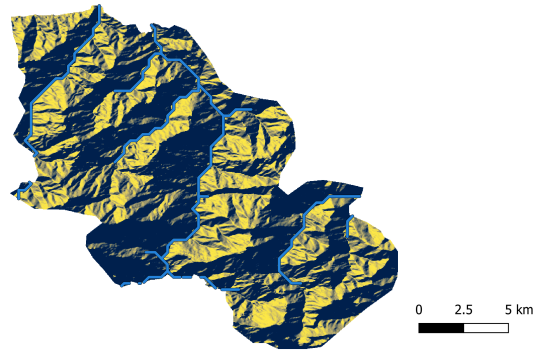


Figure 2.4. Rivers of Bozkurt.

The basin is characterized by short travel distances, steep slopes, and impermeable surfaces, which lead to high surface runoff and minimal infiltration. As a result, rainfall events quickly turn into streamflow. These conditions are ideal for flash flood generation. The streams are usually calm or low-flowing, but after just a few hours of intense rain, they can overflow dramatically. This rapid response is exactly what makes the region hydrologically sensitive. (Figure 2.5 and Figure 2.6). In this study, the SWAT model used to simulate the catchment hydrology, especially focusing on storm response and flood potential during the 2021 flood event.

Kastamonu - Basins

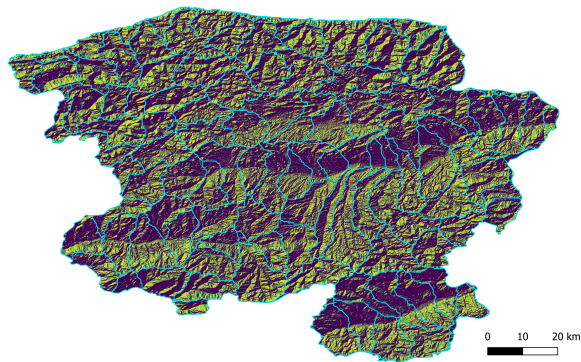


Figure 2.5. Basins of Kastamonu.

Bozkurt - Basins

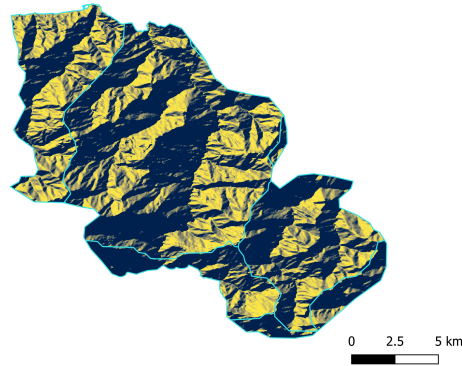


Figure 2.6. Basins of Bozkurt.

2.1.3. Climatic and Topographic Factors

Türkiye's complex topography and geographical location at the intersection of Europe and Asia have shaped its extremely varied climate, according to the Köppen Climate Classification map. Turkey's climate is classified as Mediterranean, semi-arid steppe, continental, and cold highland. (Figure 2.7 and Figure 2.8)

The Csa climate (temperate, dry summer, hot summer), which is typical of the Mediterranean zone, predominates in the coastal regions, especially along the Aegean, Mediterranean, and portions of the Marmara. The climate of the Black Sea coast is Cfb (temperate, no dry season, warm summer), with year-round precipitation. Moving inland, Central Anatolia primarily exhibits a BSk climate (cold semi-arid steppe), reflecting dry conditions and continental influence. The Dsa, Dsb, and Dsc climate types (cold, dry summer types) are prevalent in Eastern Anatolia, indicating long, cold winters and dry summers brought on by high elevation. More continental influences are suggested by the small areas of Dfa and Dfb climates (cold, no dry season, hot or warm summers) that appear in the northeast. With direct effects on agriculture, water resources, and the risk of natural hazards like floods and droughts.

Köppen Climate Classification - Turkey

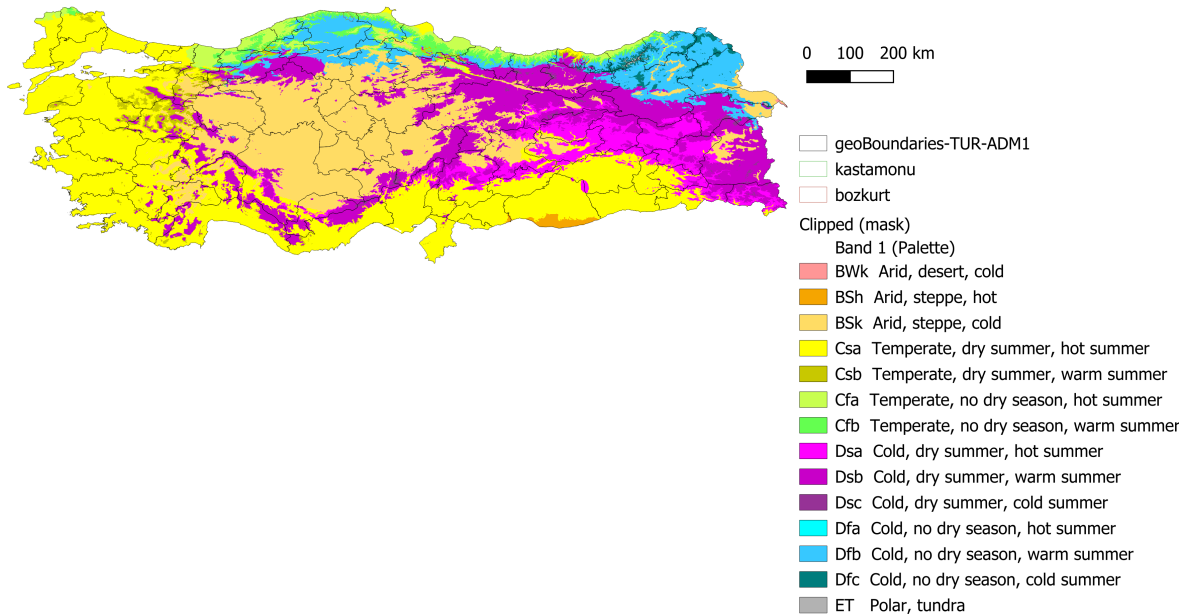


Figure 2.7. Köppen Climate Classification - Türkiye.

Köppen Climate Classification - Kastamonu

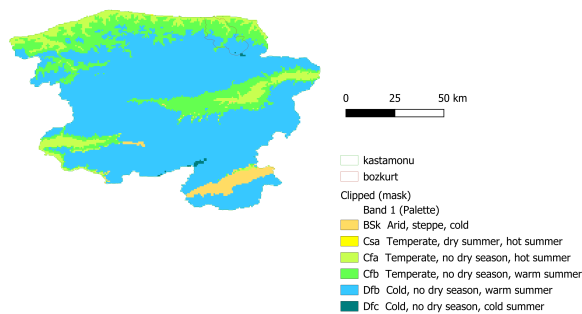


Figure 2.8. Köppen Climate Classification - Kastamonu.

Bozkurt sits at the intersection of two climate regimes — the humid Black Sea climate and the drier Central Anatolian climate. According to the Köppen-Geiger classification, the current climate is mostly Cfa (humid subtropical), with Cfb (oceanic) features at higher altitudes [47]. The Küre Mountains strongly influence this micro-

climate (Figure 2.9). While they block some of the Black Sea moisture inland, they also cause orographic rainfall, especially during convective summer storms and frontal systems in spring and autumn.

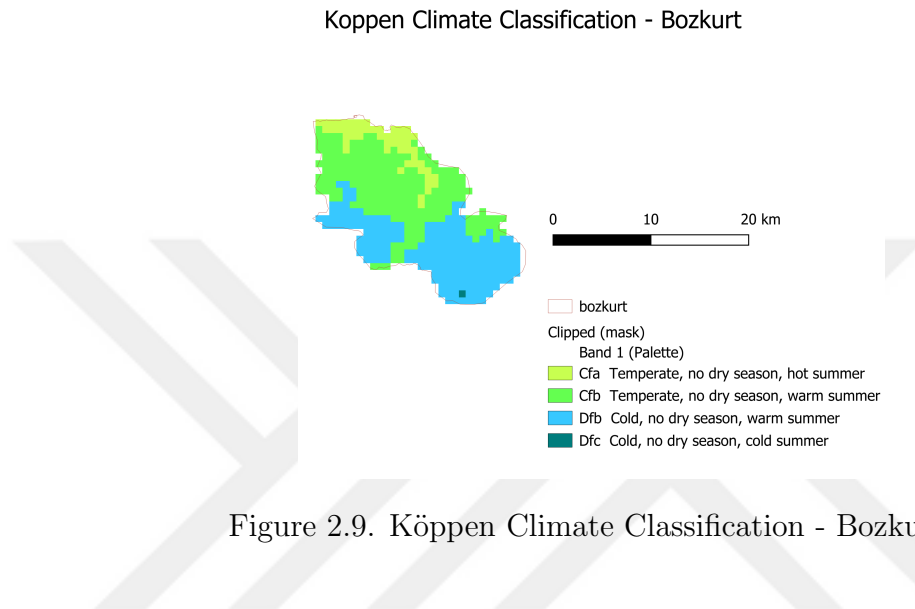


Figure 2.9. Köppen Climate Classification - Bozkurt.

Based on ERA5 reanalysis data [48], the region receives about 1000–1100 mm of precipitation annually, with peaks in April–May and October–November. However, the most dangerous floods are caused by intense, short-term rainfall, often occurring in summer. These events are becoming more frequent with rising temperatures and increased atmospheric moisture. Temperatures typically range from 2–4°C in winter to 25–28°C in summer. Steep slopes across the basin — often greater than 30% — speed up runoff, reducing the lag time between rainfall and streamflow. These physical features, combined with climate dynamics, create an environment highly sensitive to flash flooding.

In the Figure 2.10 and Figure 2.11 world cover can be seen. Kastamonu is located in the Black Sea Region so it is characterized by dense forest areas and includes agricultural land and water bodies. Bozkurt as a part of Kastamonu, shows similar world cover characteristics. Urbanization is concentrated in one region because of the mountainous characteristic of the land. These are highly vulnerable to flooding and soil erosion, with

increased probability along the banks of the river of Bozkurt where human impact is prominent. The interaction between forest cover, agricultural land, and water bodies is very significant in shaping the landscape and resulting in environmental problems such as the hazard of floods and soil erosion.

World Cover - Kastamonu

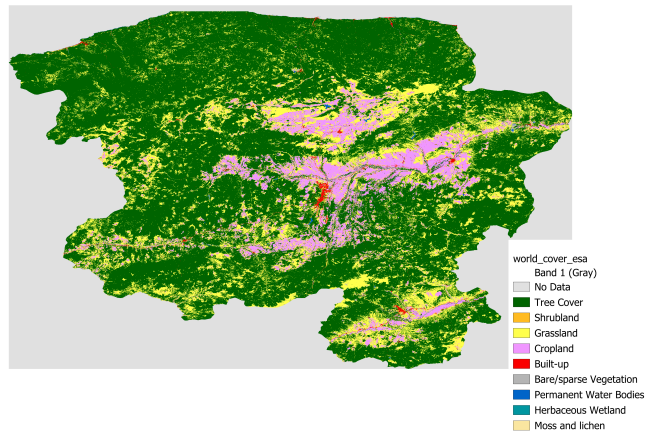


Figure 2.10. World Cover of Kastamonu.

World Cover - Bozkurt

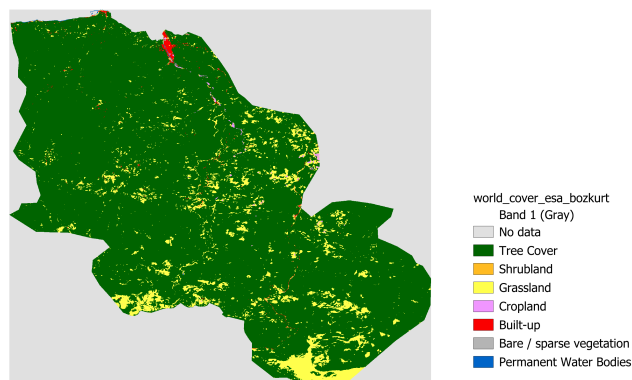


Figure 2.11. World Cover of Bozkurt.

2.1.4. Future Climate Classification

Köppen Climate Classification - Bozkurt - SSP126

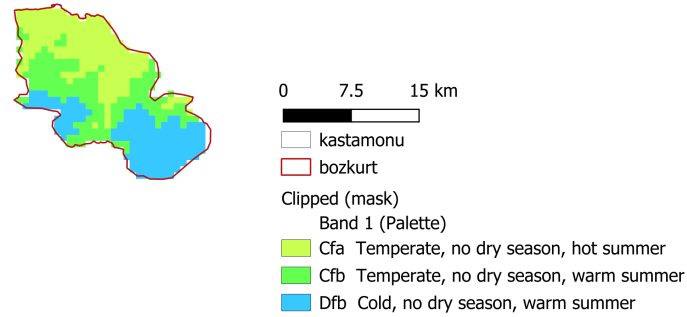


Figure 2.12. Future Climate Projection in SSP1-2.6 Scenario - Bozkurt.

According to CORDEX and RegCM5 projections under high-emission scenarios (SSP5-8.5), the Köppen climate zone for this region is expected to shift further toward Cfa, expanding into higher elevations and bringing more humid and warmer conditions[49][50]. Some higher areas currently classified as Cfb or Dfb may also experience transitions toward Cfa or even BSk (semi-arid), depending on precipitation variability (Figure 2.12, Figure 2.13, Figure 2.14).

Köppen Climate Classification - Bozkurt - SSP245

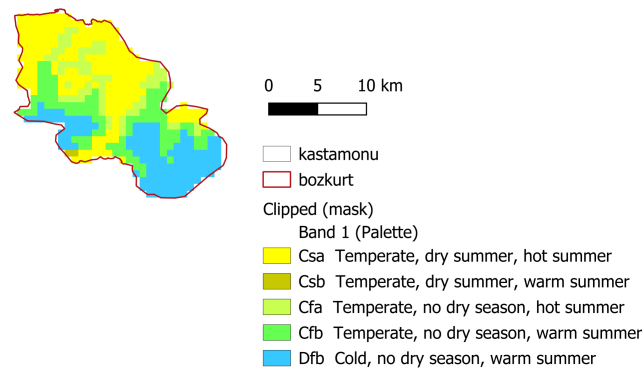


Figure 2.13. Future Climate Projection in SSP2-4.5 Scenario - Bozkurt.

Koppen Climate Classification - Bozkurt - SSP585

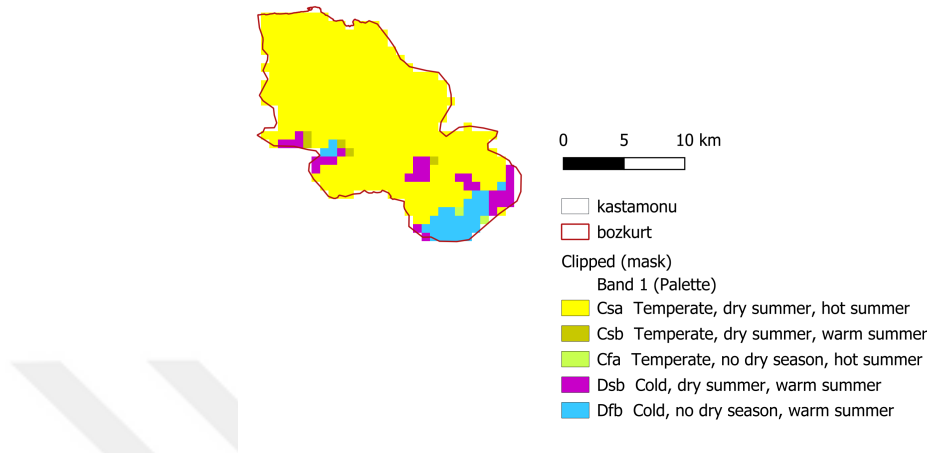


Figure 2.14. Future Climate Projection in SSP5-8.5 Scenario - Bozkurt.

This shift implies warmer, wetter summers, with increased atmospheric moisture; more intense convective storms, especially in late summer and early autumn, a rise in extreme precipitation events — a key trigger for flash floods. In short, future climate conditions are likely to increase the frequency and severity of flash floods in Bozkurt. Modeling these scenarios helps us understand how the region’s flood risk will evolve under climate change.

2.1.5. 2021 Flash Flood Event Overview

The August 2021 Bozkurt flood was one of Türkiye’s deadliest recent flash flood events. On August 11–12, heavy rainfall affected the Ezine Basin, leading to extreme flooding across the district. According to AFAD (2021) and TSMS, the area received over 400 mm of rainfall within 48 hours, mostly driven by stationary convective systems that intensified over the Küre Mountains.

The Ezine stream rapidly overflowed, sweeping through the town center with massive force. Buildings collapsed, vehicles were dragged into the water, and bridges were destroyed. According to official records, 82 people lost their lives in Kastamonu

and neighboring provinces. The event also caused widespread damage to housing, roads, and communication infrastructure.

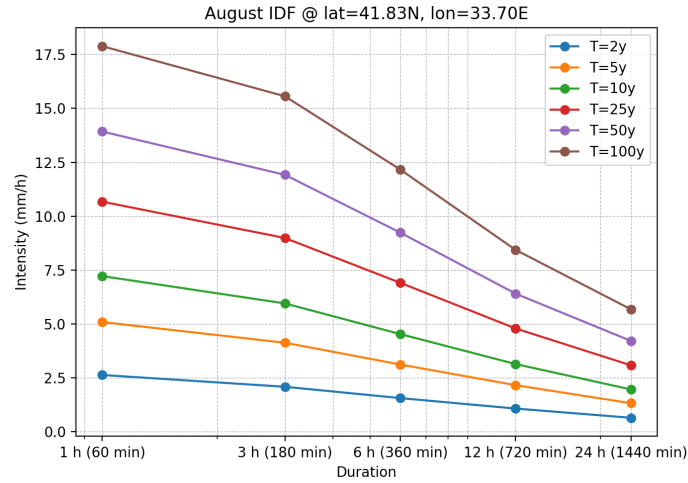


Figure 2.15. Intensity-Duration-Frequency Graph - Bozkurt.

Several studies and meteorological bulletins show that the combination of intense rainfall, steep topography, narrow valleys, and limited warning systems significantly amplified the disaster [46][51]. This flood was a clear example of a flash flood, with rapid onset, high intensity, and limited lead time for response.

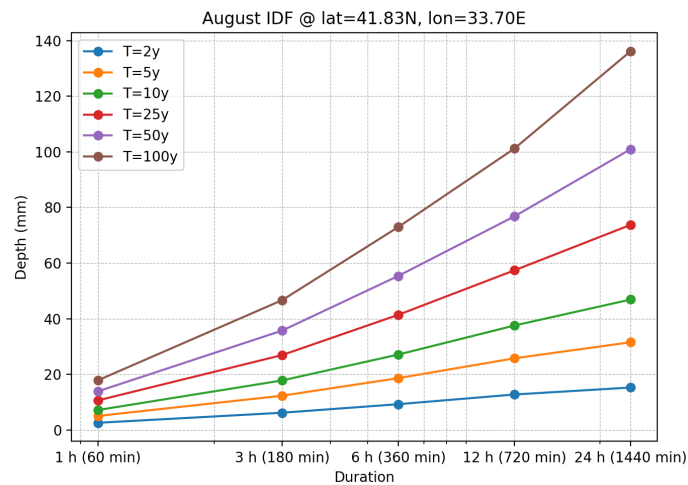


Figure 2.16. Depth-Duration-Frequency Graph - Bozkurt.

The August IDF curves for the Küre Mountains–Bozkurt region (Figure 2.16 and Figure 2.15) provide a quantitative framework to understand why this event was so destructive. Based on long-term August climatology, a 1-hour rainfall with a 100-year return period reaches around 18 mm/h, and a 24-hour event reaches about 135 mm. In contrast, the August 2021 Bozkurt flood exceeded these 100-year thresholds for multiple durations, particularly in the 6–12 hour range.

This indicates that the event was not only extreme in total accumulation but also in short- to medium-duration intensity—conditions that strongly favor rapid runoff and flash flooding in steep, confined catchments like the Ezine Basin. By surpassing the climatological envelope of August rainfall, the 2021 event underscores the region’s vulnerability to high-intensity summer storms, especially under a warming climate that increases atmospheric moisture and convective potential.

This disaster forms the central case of this thesis. By simulating it using regional climate model outputs (RegCM5) and basin-scale hydrological modeling (SWAT), I aim to analyze the key drivers and propose future-oriented adaptation strategies for flash flood risk in Bozkurt.

2.2. Hydrological Model Description

Understanding the dynamics of surface water through hydrological modeling is an essential part of modern environmental studies. Hydrological models help decision-makers in water resource management and land use planning. They are also widely used by researchers to simulate hydrological problems such as flood risk, soil erosion, and nutrient pollution.

In this case-study, I used the Soil and Water Assessment Tool (SWAT), developed by the USDA Agricultural Research Service (ARS). SWAT is a semi-distributed, process-based model that is widely applied around the world to predict the impact of land management practices on water, sediment, and agricultural chemical yields

in large and complex watersheds[52][53]. It allows the simulation of several interconnected processes including hydrology (surface runoff, groundwater flow, evapotranspiration, infiltration); weather (precipitation, temperature, solar radiation, wind speed, humidity); soil and sediment transport (erosion, deposition, and soil temperature); crop growth and agricultural practices (yield estimation) and nutrient and pesticide dynamics (nitrogen and phosphorus cycles, pesticide fate). The core concept of SWAT is the division of a watershed into sub-basins, which are further divided into Hydrologic Response Units (HRUs). Each HRU is defined by a unique combination of land use, soil type, and slope class. This structure allows the model to capture the spatial variability of the watershed and simulate the water cycle accordingly.

Although SWAT was originally developed for long-term hydrological assessments rather than short-term flood forecasting, its flexible structure makes it possible to study flood events when supported by high-resolution inputs — especially fine-scale land use maps, high-resolution DEM data, and accurate weather data. While the model runs on a daily time step, several studies have shown that it can still provide meaningful results for peak flow estimation and flood-sensitive areas when applied carefully [54][55].

In this thesis, SWAT was selected specifically because of its ability to model spatial heterogeneity in steep basins like Bozkurt, where land cover, topography, and soil properties vary significantly over short distances. This is essential for understanding the response of the Ezine stream basin, which flooded in 2021. The steep terrain, fast runoff conditions, and limited infiltration make Bozkurt highly suitable for such a physically-based approach.

For this study, SWAT was used through the QSWAT plugin, which integrates SWAT with QGIS — a free and open-source Geographic Information System. QSWAT allows users to input spatial data (e.g., DEM, land use, soil maps), define sub-basins, delineate HRUs, and prepare weather inputs for simulation. QGIS is widely used in environmental modeling because of its accessibility, community support, and compatibility with tools like SWAT. Compared to commercial GIS software, it offers a

cost-effective and flexible alternative, especially suitable for academic research.

SWAT requires several input datasets, such as: digital elevation model (DEM) to define watershed boundaries and stream networks, land use and land cover (LULC) to estimate vegetation impact and human activity, soil data including physical and chemical properties, and climate Data: daily precipitation, temperature, humidity, solar radiation, and wind.

While QSWAT makes the workflow manageable, it is important to note the model's limitations. SWAT does not simulate urban drainage systems or floodplain dynamics, and its daily timestep may miss the peak discharge of extremely short flash flood events. Therefore, the results must be interpreted with an awareness of these limitations.

Despite these constraints, SWAT remains one of the most widely used and validated watershed-scale hydrological models. When applied correctly, it provides valuable insight into water balance, runoff patterns, and the spatial behavior of flood-prone regions like Bozkurt.

2.3. Climate Model Description

Climate represents the long-term patterns of temperature, precipitation, humidity, and wind in a region. Understanding a region's climate requires the consideration of complex physical processes, including interactions between the atmosphere, oceans, land surfaces, and biosphere. These components interact through dynamic feedback loops, such as cloud cover (negative feedback) or ocean warming and CO₂ absorption (positive feedback), which can either stabilize or amplify climatic changes[20].

Due to this complexity, predicting climate trends is a challenging task. Climate models have become essential tools for studying the climate system, projecting future conditions, and evaluating the impacts of various climate drivers. These models are

mathematical representations of climate processes, grounded in physics, chemistry, and biology. Different levels of complexity exist, and the selection of the model depends on the study's objective, available computational resources, and spatial/temporal resolution needs [50][56]. There are four main categories of climate models, explanation of the models shown in the Table 2.1.

Table 2.1. Climate Model Types.

Model Type	Description	Spatial Resolution	Applications	Example Models
Energy Balance Models (EBMs)	Simplified models based on the balance between incoming and outgoing radiation.	Zonal/Global	Estimating temperature response to CO ₂	Budyko Model
Intermediate Complexity Models (ICMs)	Include more processes like ocean-atmosphere coupling but with simplified physics.	Global or Regional	Paleoclimate studies	Bern Carbon Cycle Model
General Circulation Models (GCMs)	Simulate 3D atmospheric and oceanic processes on global scale.	~100–200 km	Climate projections, IPCC reports	HadGEM, GFDL, MPI-ESM
Earth System Models (ESMs)	Include full carbon, sulphur, and other biogeochemical cycles in addition to GCM processes.	Global/Regional	Climate impact assessment	CESM, CMIP6

While GCMs and ESMs are widely used in large-scale assessments like the IPCC, their spatial resolution is often too coarse to simulate local or extreme events like flash floods. For such events, regional modeling becomes essential.

2.3.1. Regional Climate Models

To obtain more localized information, Regional Climate Models (RCMs) are used to downscale the output of GCMs. RCMs simulate climate processes over a limited area at higher spatial and temporal resolution. This approach, known as dynamical downscaling, is critical for studying local-scale extremes such as flash floods, which

often occur within areas of less than 100 km^2 and evolve in under 6 hours [57][58].

RCMs operate by using lateral boundary conditions provided by a global model. This makes the accuracy of boundary inputs especially important—particularly for hydrostatic cores, which are more stable for large domains but less accurate for vertical dynamics. To overcome this, newer RCMs like RegCM5 allow simulations using a non-hydrostatic core, which better captures vertical accelerations and processes such as deep convection. In this study, RegCM5 with the MOLOCH non-hydrostatic core is used to simulate high-intensity rainfall events in Bozkurt, Kastamonu — a small, steep catchment affected by flash floods.

RegCM5 is part of the ICTP regional climate modeling system. It supports both hydrostatic and non-hydrostatic dynamics, depending on the resolution and core selected. The MOLOCH core, in particular, supports convection-permitting (CP-RCM) simulations at spatial resolutions of 4 km or finer. These simulations explicitly resolve convective systems without needing parameterization [59], making them ideal for flash flood studies.

However, CP-RCMs are computationally expensive and require very high-resolution input data, large domain size to allow full development of convective systems such as a spin-up distance of at least 150 km is required [60][61] and a domain of at least $300 \times 300 \text{ km}$ is often recommended [62].

Despite their computational demands, CP-RCMs add significant value. Studies show that models operating at resolutions finer than 10 km (ideally 4 km or less) can better capture the intensity, spatial structure, and timing of extreme precipitation, especially over mountainous areas [58][59][63].

2.3.2. Application to Bozkurt

The study area, Bozkurt in Kastamonu, is a small mountainous region with two key streambeds — Ezine and İlişi — both prone to flash floods. Given the narrow valleys, steep topography, and rapid hydrological response, high spatio-temporal resolution is essential for realistic modeling. In this research, RegCM5 with the MOLOCH non-hydrostatic core, driven by ERA5 reanalysis data is used on a high-resolution grid. The aim is to simulate intense summer rainfall events with a convection-permitting approach, improving the accuracy of precipitation forecasts and supporting hydrological modeling with the SWAT model.

This setup allows the climate model to directly resolve deep convective systems responsible for the 2021 flash flood in Bozkurt. Compared to coarser models, this approach provides better support for early warning, disaster preparedness, and flood risk analysis in small, data-scarce basins.

2.4. Flash Flood Potential Index (FFPI)

In the context of this study, FFPI was selected for its suitability in small basins with steep terrain and high flash flood frequency. Future work may incorporate other indices, particularly FFG, in a real-time forecasting framework.

The FFPI provides a relative measure of flash flood susceptibility by combining several static and dynamic variables, each of which contributes to the generation or amplification of surface runoff. These variables are often standardized and weighted according to their influence. While the specific formulation may vary, the index typically includes the following components:

- **Rainfall Intensity:** Flash flood initiation is highly sensitive to the rate of precipitation over short time intervals. Rainfall exceeding 50 mm/hour is commonly used as a threshold for flash flood triggering, particularly in steep or urbanized

regions [58][59].

- **Soil Moisture Content:** Antecedent wetness conditions are crucial in determining infiltration capacity. When soils are already saturated $> 80\%$, the risk of flash flooding increases significantly, as most precipitation converts to surface runoff [16].
- **Surface Runoff:** Runoff depth derived from hydrological models (e.g., SWAT or SCS Curve Number Method) reflects the basin's response to rainfall. High surface runoff values indicate limited infiltration and elevated flood risk.
- **Topographic Parameters:** Terrain slope, curvature, and drainage density affect water movement and concentration times. Steep slopes $> 30\%$ and dense drainage networks $> 2 \text{ km/km}^2$ reduce travel time and intensify flow accumulation [64].
- **Atmospheric Moisture Variables:** Indicators such as Convective Available Potential Energy (CAPE), precipitable water, or relative humidity signal the likelihood of deep convection and storm development.

In this study, a simplified version of the FFPI was developed by combining key variables available from the SWAT model, ERA5 climate reanalysis, and topographic analysis using QGIS. All input layers were normalized, and weights were assigned based on sensitivity observed in previous literature [19][65].

2.4.1. Application of FFPI in Bozkurt

Bozkurt was severely affected by a flash flood in August 2021, where rainfall exceeded 400 mm over 48 hours, with hourly intensities over 70 mm. Model outputs from SWAT, combined with ERA5 soil moisture reanalysis, indicate that all major FFPI parameters reached critical values during the event. The Table 2.2 below summarizes the values used in the FFPI classification for Bozkurt.

Table 2.2. Flash Flood Risk Indicators and Thresholds.

Parameter	Observed/Modeled Value	Threshold	Risk Category
Rainfall Intensity	>70 mm/h	>50 mm/h	Very High
Soil Moisture (ERA5)	>85%	>80%	Very High
Surface Runoff (SWAT)	>22 mm/h	>10 mm/h	Very High
Mean Slope	35–45%	>30%	Very High
Drainage Density	>2.5 km/km ²	>2.0 km/km ²	High

These results suggest that Bozkurt falls into a very high FFPI risk class, particularly in the upstream sub-basins of the Ezine stream, where steep slopes and saturated soils dominate. The FFPI-based findings align closely with the observed impact of the 2021 flood.

Table 2.3. FFPI Comparison Between Other Districts of Kastamonu

District	Slope (%)	Max Rainfall (mm/h)	Runoff Potential	FFPI Classification
Bozkurt	35–45	>70	High	Very High
Tosya	15–25	~35	Moderate	Moderate
İnebolu	10–30	45–50	Moderate–High	High
Devrekani	10–15	~30	Low	Low

To provide context in Table 2.3, the FFPI scores for Bozkurt were compared with other districts in Kastamonu Province. This comparison confirms that Bozkurt exhibits a more hazardous combination of factors contributing to flash flood risk than neighboring regions. The FFPI approach provides spatial insight into where rapid runoff generation is most likely, supporting regional prioritization for mitigation or early warning efforts.

2.5. Study Design

This study aims to model and analyze flash flood events in Bozkurt, Kastamonu — a region with complex topography and high flood vulnerability — by integrating high-resolution regional climate simulations with physically-based hydrological modeling. The methodology is designed to capture the key drivers of flash flood generation, including intense convective rainfall, steep terrain, and rapid surface runoff. Architectural design of the study can be seen in Figure 2.17

The climate data used in this study was generated through the Regional Climate Model (RegCM5), configured with a non-hydrostatic dynamical core and convection-permitting resolution (CP-RCM). This setup enables the model to explicitly resolve convective processes such as deep summer storms without relying on convective parameterization schemes. This is particularly important for flash flood research, as these events often develop within small spatial and temporal scales [63][59].

The RegCM5 simulations were run over a limited-area domain centered on Bozkurt, with a horizontal resolution of less than 10 km and 15-minute, 1 hour, 3 hour, 4 hour and 6 hour temporal output frequency. This high temporal resolution was selected to capture rapid changes in atmospheric conditions that are typically missed in coarser datasets. Boundary conditions were provided by the ERA5 reanalysis dataset, and land surface processes were modeled using CLM4.5.

To simulate the hydrological response of the catchment, the Soil and Water Assessment Tool (SWAT) was employed. SWAT is a semi-distributed, process-based model developed to evaluate the impact of land use and management practices on water flow, sediment transport, and nutrient dynamics. It is well-suited for simulating long-term watershed-scale processes, but recent studies have also demonstrated its capacity to capture short-term events like flash floods when supported by high-resolution climate inputs [53][54].

Workflow of Coupled CP-RegCM5 and QSWAT+ for Flash Flood Modeling

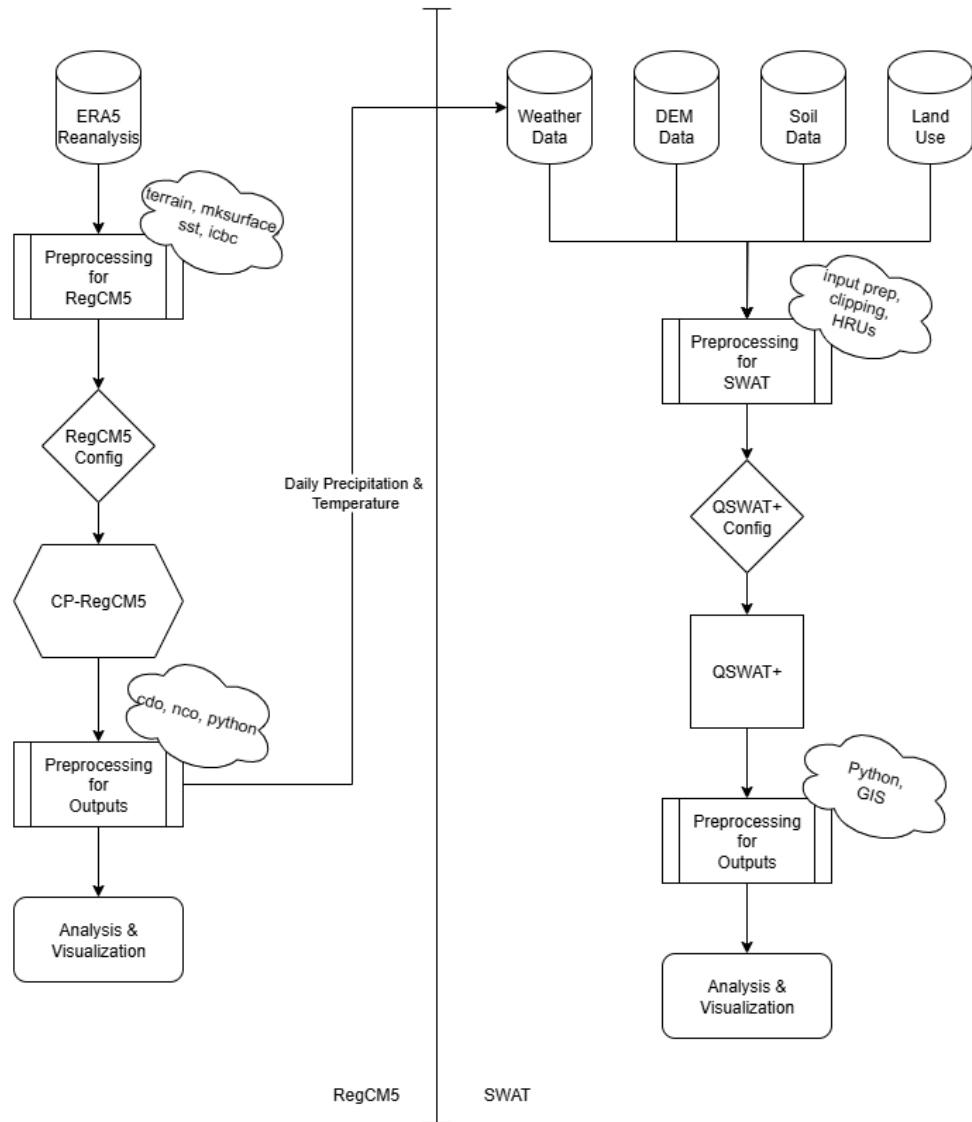


Figure 2.17. Study Design.

The Ezine stream basin, which flooded in 2021, was delineated as the primary hydrological unit. The model was calibrated to reproduce known flow responses and validated using both literature and event-based runoff analysis.

The main objective of this study is to simulate and assess the flash flood potential in Bozkurt by coupling high-resolution climate projections with hydrological modeling. By doing so, the research aims to; improve the representation of extreme rainfall events in complex terrains, analyze the hydrological response under intense, short-duration

precipitation, quantify flash flood risk using spatially explicit indicators (e.g., surface runoff, FFPI), provide insights into the role of climate variability and topography in flood generation

This approach contributes to the growing body of research focused on down-scaling climate model outputs for disaster risk analysis. The findings are expected to support regional flood risk assessments, improve early warning capacity, and inform local decision-making for disaster preparedness and mitigation.

2.6. Data Preparation

In order to run the SWAT model effectively, it is essential to collect, preprocess, and organize spatial and temporal datasets related to topography, land use, soil characteristics, and meteorological conditions. This section outlines the datasets used in this study, their sources, and the procedures followed for preparing them for input into the QSWAT+ interface. SWAT+ needs spatial data such as digital elevation model (DEM), land use/land cover maps and soil maps. Detailed data sources can be found in Table 2.4.

The NASA Shuttle Radar Topography Mission (SRTM) Global dataset, which is made available by OpenTopography, provided the topographic data. The dataset offers continuous elevation coverage appropriate for slope analysis and watershed delineation, with a spatial resolution of 30 meters. For consistency with other spatial datasets, the DEM was reprojected to the proper coordinate reference system (UTM Zone 37N, WGS84 datum) after being clipped to the study area using QGIS. The watershed boundaries, stream network, and slope classes needed for Hydrologic Response Unit (HRU) definition were then defined in QSWAT+ using the processed DEM [66].

The European Space Agency (ESA) WorldCover 10 m 2021 product, which offers global land cover classification at a 10-meter spatial resolution, provided the land use and land cover (LULC) data. The official ESA WorldCover portal provided the dataset

for download. Based on Sentinel-1 and Sentinel-2 satellite imagery, it comprises 11 land cover classes, including urban areas, water bodies, forests, and cropland.

Using QGIS, the original raster was clipped to the study area and then reprojected to the UTM Zone 37N coordinate system (EPSG:32637). Then, in order to enable HRU (Hydrologic Response Unit) definition in QSWAT+, the land cover classes were reclassified using the SWAT land use code system. Using QGIS's raster calculator, reclassification was carried out according to SWAT's mandated land use categories (e.g., URBN for urban, AGRL for agriculture, FRST for forest, etc.) [67].

The soil-related data came from SoilGrids 2.0, which is a global-level gridded soil information system developed by ISRIC [75] – World Soil Information, and has been accessed for this information from its URL: <https://soilgrids.org>. SoilGrids provides predictions for several soil properties at six standard depth intervals—from 0 to 5 cm, 5 to 15 cm, 15 to 30 cm, 30 to 60 cm, 60 to 100 cm, and 100 to 200 cm, with a spatial resolution of 250 meters.

For the purpose of this study, soil variables considered significant for SWAT modeling such as sand, silt, and clay texture, bulk density, organic carbon, pH, and cation exchange capacity (CEC) were extracted for each depth layer. Using QGIS, these raster layers were clipped according to the watershed boundary, and the mean values of the upper soil layers (usually 0–30 cm) were calculated.

Next, the prepared soil data were converted into a simulating format of a SWAT soil file (.sol file) using either the QSWAT+ Soil Editor or by joining the raster-derived values to a polygon shapefile representing soil mapping units. Further, soil IDs were assigned according to each polygon mapping unit, thereby linking each unit with the physical and chemical properties required by SWAT's soil database [68].

Table 2.4. Data Sources Used in This Study

Data Type	Source	Resolution	Format
DEM	NASA SRTM (2013), via OpenTopography DOI: https://doi.org/10.5069/G9445JDF	30 meters	GeoTIFF (.tif)
Land Use / Land Cover	ESA WorldCover 2021 https://esa-worldcover.org	10 meters	GeoTIFF (.tif)
Soil	SoilGrids 2.0 (ISRIC) https://soilgrids.org	250 meters (0–30 cm depth)	GeoTIFF (.tif) / CSV
Weather (Reanalysis)	ERA5 (ECMWF), via CDS API [Hersbach et al., 2020]	0.25° (hourly, multiple pressure levels)	NetCDF (.nc)
Weather (Down-scaled)	RegCM5 outputs (this study) [Giorgi et al., 2023]	4 km (4-hourly)	NetCDF / TXT

To generate high-resolution meteorological input for the SWAT model, a regional climate simulation was performed using the RegCM5 model with ERA5 reanalysis data as boundary and initial conditions. ERA5 is the fifth-generation atmospheric reanalysis dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). It provides hourly data from 1940 to the present, globally gridded at $0.25^\circ \times 0.25^\circ$ resolution, and includes a wide range of surface and upper-atmosphere variables distributed across multiple pressure levels.

For this study, ERA5 reanalysis data was acquired for a regional domain bounded by 42.2°N – 40.59°N latitude and 31.88°E – 35.48°E longitude. The selected atmospheric variables were: geopotential height (for vertical structure and terrain influence), zonal wind (u component) and meridional wind (v component) (for horizontal wind dynamics), temperature, and specific humidity [47].

These variables were used to initialize and drive the RegCM5 model, which was configured with the non-hydrostatic MOLOCH core, 4 km horizontal resolution, and 37 vertical levels. This dynamic downscaling process enabled a more realistic representation of local topographic and mesoscale atmospheric patterns relevant to flash flood generation [33].

The RegCM output was then post-processed to extract daily precipitation and temperature values at the subbasin level. These time series were formatted into SWAT-compatible input files (.pcp and .tmp) using custom scripts and were assigned to representative subbasins within the QSWAT+ interface. Where required, the SWAT weather generator was used to fill in missing or incomplete data series. This approach ensured that the model incorporated physically consistent, spatially resolved weather data capable of capturing the local hydrometeorological conditions that lead to flash flood events.

3. RESULTS

Based on all test runs that can be seen in Figure 3.1. Consider the following naming convention in Table 3.1.

RegCM5 with the MOLOCH non-hydrostatic core performed well in detecting flash flood events, particularly in representing high-intensity rainfall and capturing the timing of convective precipitation. Three different spatial resolutions — 6 km, 4 km, and 2 km — were primarily tested. With increasing resolution, a clear improvement was observed in both the spatial structure and timing of precipitation. In particular, the 2 km resolution run captured the convective system more accurately over the Küre Mountains, where the actual rainfall event was observed to develop.

Nevertheless, even in the best-performing simulations, shifts in both the timing and spatial distribution of precipitation were observed. In several cases, the most intense rainfall occurred a day earlier or later than the actual flood event. In others, precipitation was concentrated outside the Bozkurt basin, despite the fact that the general structure of the convective system appeared visually realistic. These spatial and daily-scale temporal errors are commonly reported in regional climate model studies, especially in complex terrains such as mountainous regions, where even small inaccuracies in topography or storm triggering can lead to large differences in runoff generation and flood behavior.

To better analyze the temporal evolution of the event, model outputs were produced at five different time intervals: 15-minute, 1-hour, 3-hour, 4-hour and 6-hour. It was found that the 15-minute outputs were critical for identifying the short (Figure 3.2 and Figure 3.3), intense bursts of rainfall that triggered the flash flood. While 1-hour outputs remained useful, 3- and 6-hour outputs tended to smooth out peak intensities and missed important short-duration events. Therefore, high-frequency outputs were considered essential for understanding flash flood mechanisms in small, steep basins

such as Bozkurt—even though they resulted in larger data volumes and longer processing times.

The placement of the flood basin within the model domain also significantly influenced simulation outcomes. In earlier tests, Bozkurt was positioned too close to the lateral boundaries of the domain. As a result, the simulated rainfall was either weak or incorrectly located. After the basin was relocated to the domain center—well away from the relaxation zones—the spatial accuracy of precipitation patterns improved notably. These findings highlight the sensitivity of MOLOCH-based nonhydrostatic simulations to domain boundary effects and underscore the importance of internalizing key regions within the active domain.

During high-resolution runs, a technical error known as RSUB_TOP drainage error was encountered. This error is generally linked to inconsistencies or extreme gradients in soil and topographic input data. It was observed to occur especially in configurations with steep terrain or fine vertical discretization. In some cases, reducing the model time step helped to avoid the error, while in others, adjustments to surface or vertical parameter files were required. Although it was manageable, the RSUB_TOP error resulted in delays and additional computational effort throughout the testing phase.

In terms of numerical stability, a time step of 1 second ($dt = 1s$) was applied in most simulations to prevent CFL (Courant – Friedrichs – Lewy) violations. Even at 4 km resolution, time steps greater than 5 seconds led to model crashes. This configuration, although computationally expensive, was considered necessary for properly resolving convective-scale processes and ensuring model convergence.

Different microphysics schemes were also tested to find their influence on flood representation. Among the available options, WSM5 ($ipptls = 3$) was found as the most realistic precipitation patterns in both intensity and structure for detecting flash floods in an area like Bozkurt. Especially at 2 km resolution, WSM5 provided clear

convective cell development over the flood basin, closely matching the observed storm behavior. Other schemes either overestimated the rainfall or produced overly smooth fields that failed to reflect the rapid onset and peak intensity associated with the flood event. Consequently, WSM5 was adopted as the default scheme in subsequent runs. The Emanuel convection scheme ($\text{icup} = 4$) was also included in the configuration, but, as expected under nonhydrostatic conditions, its impact was minimal since deep convection was explicitly resolved by the MOLOCH core. These results confirm that, in convection-permitting models, microphysics plays a more dominant role than cumulus parameterization in controlling storm dynamics.

Even under the best configuration, flood peak timing was not always reproduced accurately. In some runs, the triggering rainfall arrived too early or too late compared to the observed event. This confirms that, although RegCM5 with MOLOCH can simulate convective systems with high detail, uncertainties remain regarding the exact timing and localization of storm events. Therefore, results must be interpreted cautiously, particularly when the model is used in operational contexts or for early warning systems.

Table 3.1. Naming convention for simulation runs

Field	Description
centerNameInitial	e.g. b (Bozkurt), k (Küre)
spatialResolution	2km
modelOutput	15min
gridSize	75x75
monthFrame	5–8 (May–Aug 2021)
optionalNotes	optional parameters

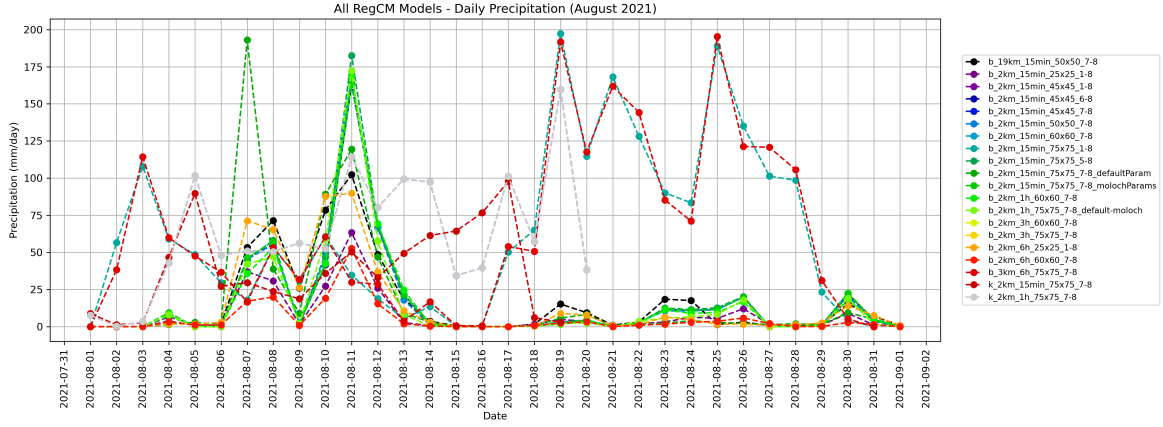


Figure 3.1. CP-RegCM Simulation Results.

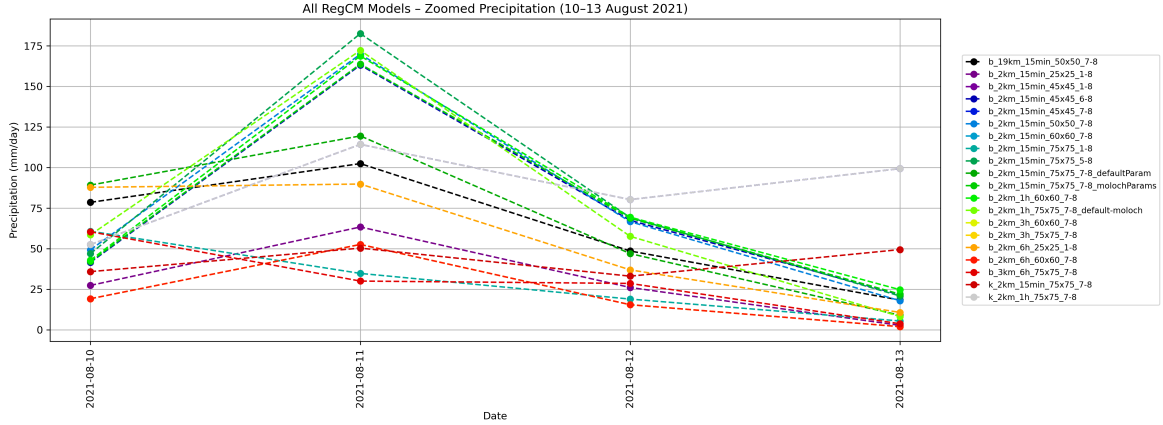


Figure 3.2. CP-RegCM Simulation Results - Event Date.

The Table 3.2 shows the statistical performance of different RegCM5–MOLOCH configurations using RMSE, Pearson correlation, and bias values. Several sensitivity tests were applied by changing domain boundary widths, time output frequencies, vertical layer settings, and model resolutions. The goal was to understand how each configuration affects the model's ability to capture the flash flood event in Bozkurt in terms of both timing and magnitude. Among all simulations, the best performance was obtained with the 15-minute output and 15-grid boundary (boundry15) setup. This configuration produced the lowest RMSE (89.27) and a high correlation (Pearson_r = 0.946), with a moderate negative bias. It was seen that when the Bozkurt basin was placed well inside the domain, away from the lateral boundary relaxation zones, the timing and intensity of rainfall improved. The default setup without extra buffer also

gave good results, especially in correlation (0.978), but had a slightly higher RMSE, suggesting that spatial structure was slightly less accurate even if the timing was better.

Table 3.2. Performance Metrics of Different RegCM5 Model Configurations

Model	RMSE	Pearson_r	Bias
b_2km_15min_75x75_5-8	89.28	0.946	-78.84
b_2km_1h_75x75_7-8_default-moloch	92.92	0.978	-84.58
b_2km_15min_50x50_7-8	93.55	0.960	-82.80
b_2km_1h_60x60_7-8	94.93	0.936	-82.26
b_2km_15min_60x60_7-8	97.10	0.942	-84.58
b_2km_15min_75x75_7-8_molochParams	97.10	0.942	-84.58
b_2km_15min_45x45_6-8	97.75	0.941	-85.27
b_2km_15min_75x75_7-8_defaultParam	109.46	0.929	-92.56
b_2km_15min_45x45_1-8	116.46	0.281	-72.11

When the boundary buffer was increased to 30 grids, or the output frequency was reduced to 1-hour, the error increased. RMSEs in these cases rose to around 93–95, and correlations dropped slightly. It was understood that while a larger boundary zone may help in general stability, it did not significantly improve the precipitation signal over Bozkurt and sometimes even weakened it. Similarly, 1-hourly outputs missed some of the short, sharp rainfall peaks observed in 15-minute data. Some tests were done by changing the input–output file configurations or turning on water–hydro coupling. These tests showed almost identical results, confirming that those specific settings had limited impact on precipitation behavior. Another experiment with reduced vertical levels (6–9 sigma levels) showed slightly higher RMSE and slightly lower correlation, but the general pattern remained similar. The 2 km resolution model, although visually promising, had a higher RMSE (109.45) and a lower Pearson_r (0.928). This suggests

that even though finer spatial resolution improves convective detail, if the setup is not well-tuned (e.g., time step, boundary, vertical levels), the timing and intensity may still shift. It was also more sensitive to RSUB_TOP errors and needed higher computational effort. The longer run, which had different initial and lateral boundary treatment, gave the worst result in this group. Its RMSE was over 116, and the Pearson correlation dropped significantly (0.28), showing that both the magnitude and the timing of the rainfall deviated strongly from the observed event. This suggests that storm triggering was either too early or too late, or the convective system formed in a displaced location.

Table 3.3. Daily Precipitation (mm) from Different RegCM5 Configurations (August 10–13, 2021)

Model	8/10/2021	8/11/2021	8/12/2021	8/13/2021
b_2km_15min_75x75_5-8	46.93	182.54	69.14	20.82
b_2km_1h_75x75_7-8_default-moloch	58.54	172.17	57.60	8.15
b_2km_15min_50x50_7-8	49.29	169.80	66.63	17.90
b_2km_1h_60x60_7-8	42.92	168.73	69.41	24.69
b_2km_15min_75x75_7-8_molochParams	42.09	163.70	68.76	21.92

Results are also compared according to their output frequency in Figure 3.4, time range in Figure 3.5 and grid size in Figure 3.6. In summary, it was observed that the best results were obtained with short time outputs (15 min), careful domain placement, and standard microphysics and vertical settings. Increasing boundary width or changing physics did not lead to major improvement. Finer resolution alone was not enough without proper tuning. When the flood basin was placed too close to the boundary or the output frequency was too coarse, both timing and magnitude performance declined.

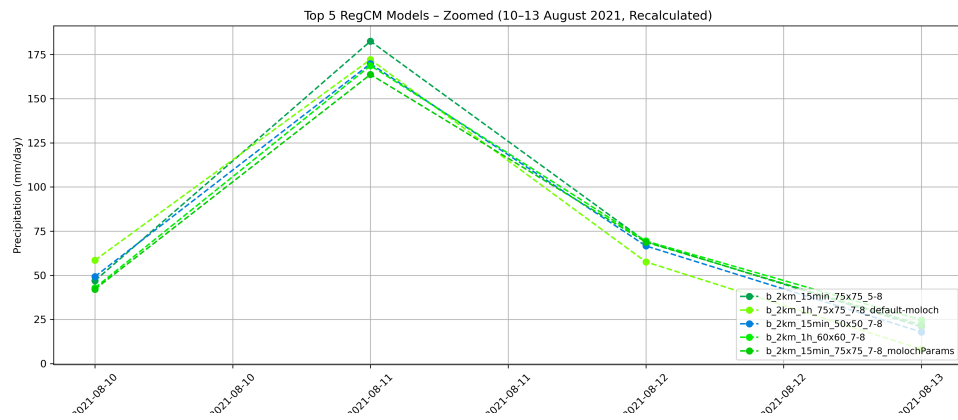


Figure 3.3. Top 3 CP-RegCM Simulation Results - Event Date.

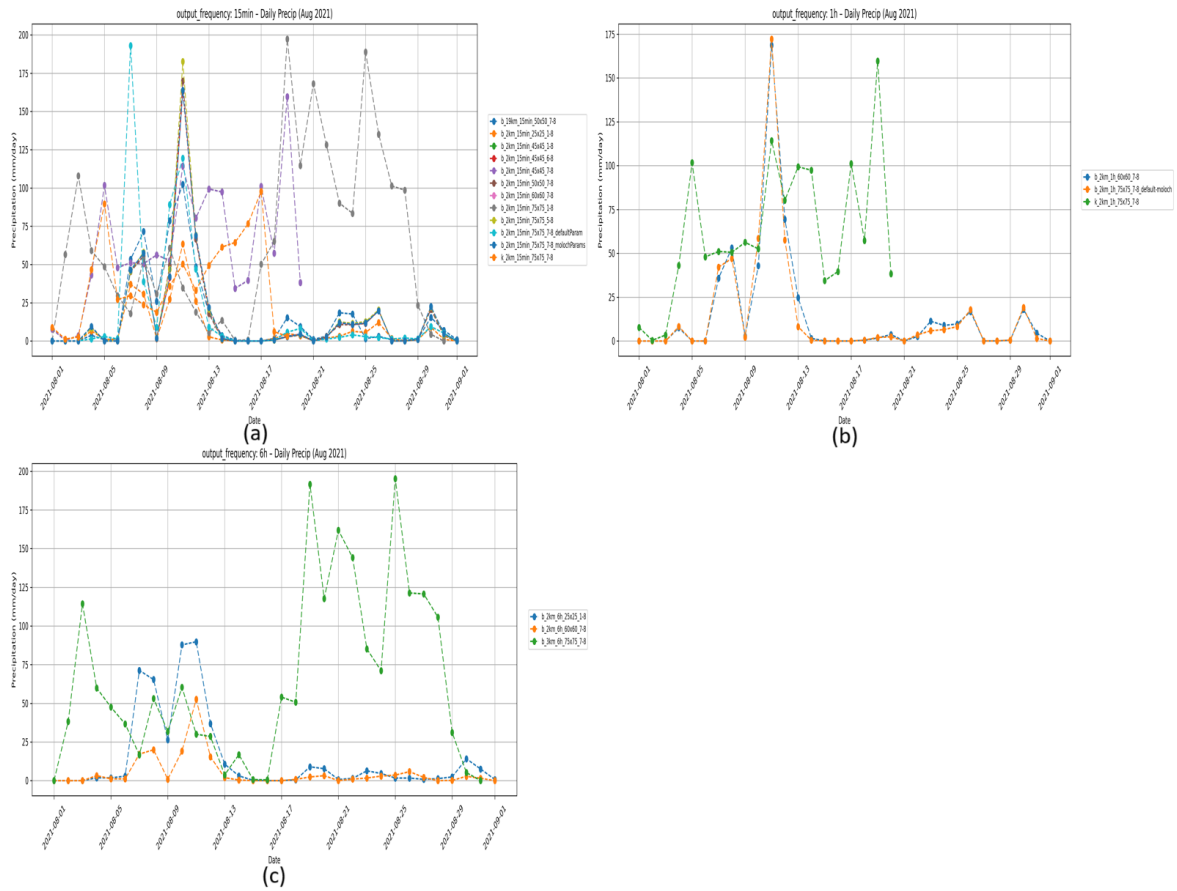


Figure 3.4. CP-RegCM Simulation Results - Grouped by Output Frequency:

(a) - 15 Minutes, (b) - 3 Hours, (c) - 6 hours.

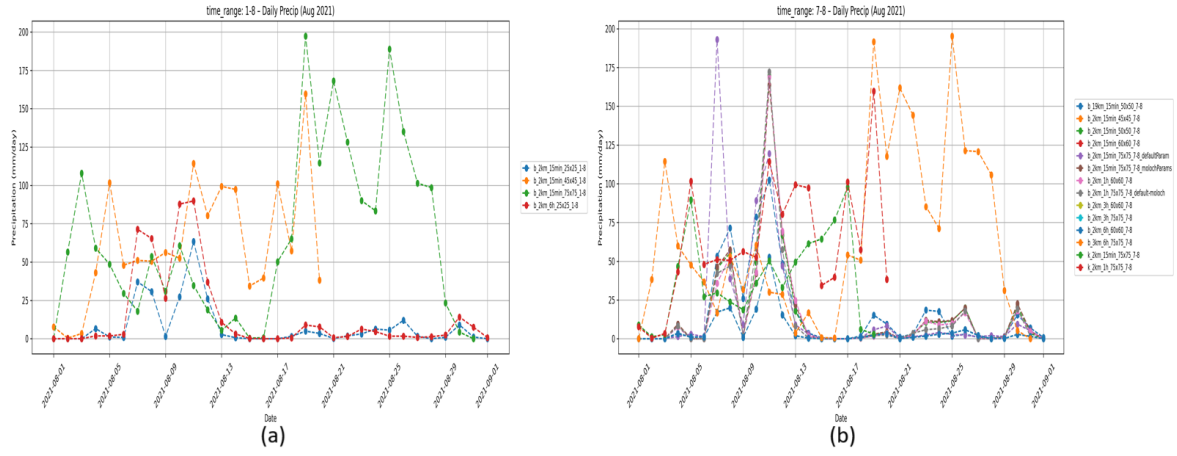


Figure 3.5. CP-RegCM Simulation Results - Grouped by Time Range:

(a) - January - August, (b) - July - August.

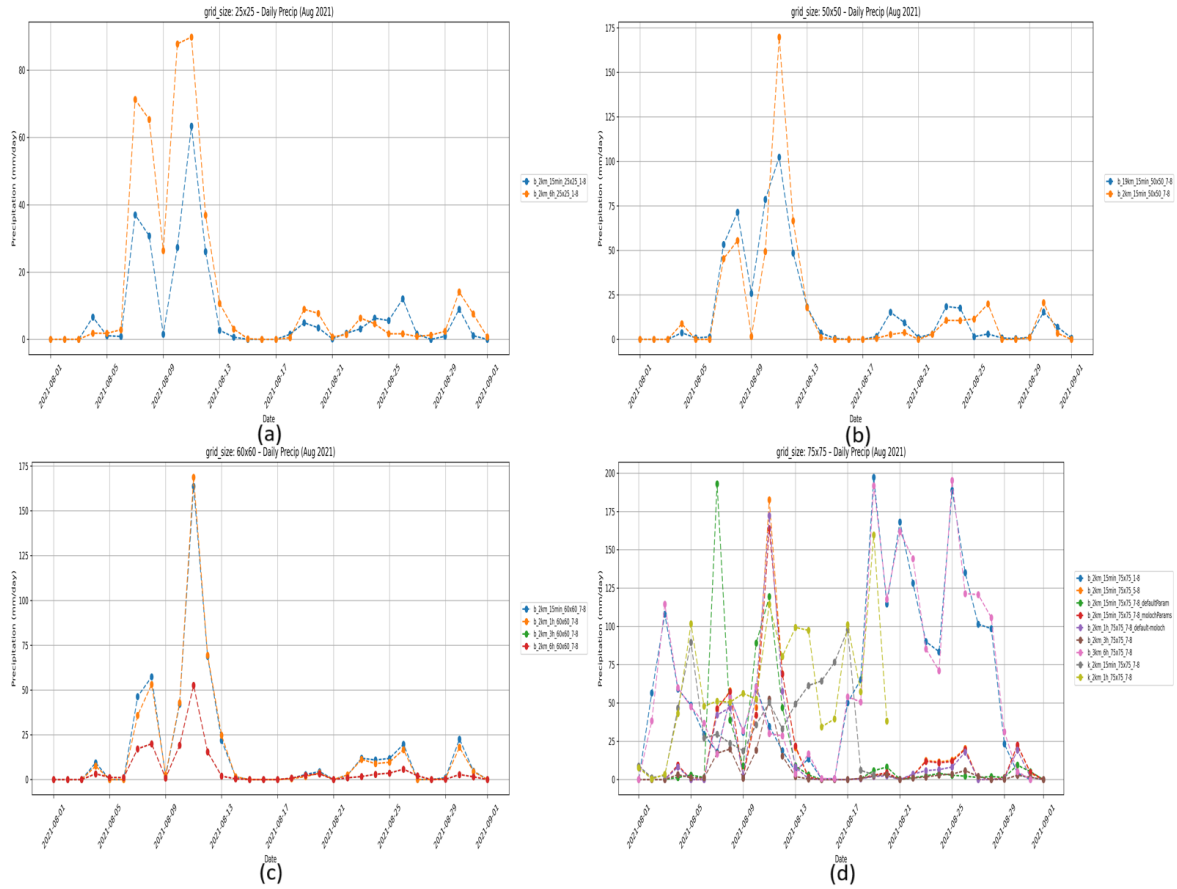


Figure 3.6. CP-RegCM Simulation Results - Grouped by Grid Size:

(a) - 25x25, (b) - 50x50, (a) - 60x60, (b) - 75x75.

The rainfall characteristics produced by all RegCM5–MOLOCH simulations were evaluated against commonly accepted flash flood thresholds to assess whether the modeled events can be classified as flash floods. According to the literature, thresholds such as > 50 mm in 1 hour, $> 60 - 70$ mm in 3 hours, and > 100 mm in 6 hours are typically used to identify flash flood conditions in steep and fast-responding basins—particularly in mountainous areas of the Mediterranean, Balkans, and Northern Anatolia. These criteria are also supported by WMO’s Flash Flood Guidance System, NOAA Atlas 14, and regional case studies from Turkey. The best resulted model’s rainfall characteristics visualized at Figure 3.7 for 1-hour, Figure 3.8 for 4-hour and Figure 3.9 for 6-hour.

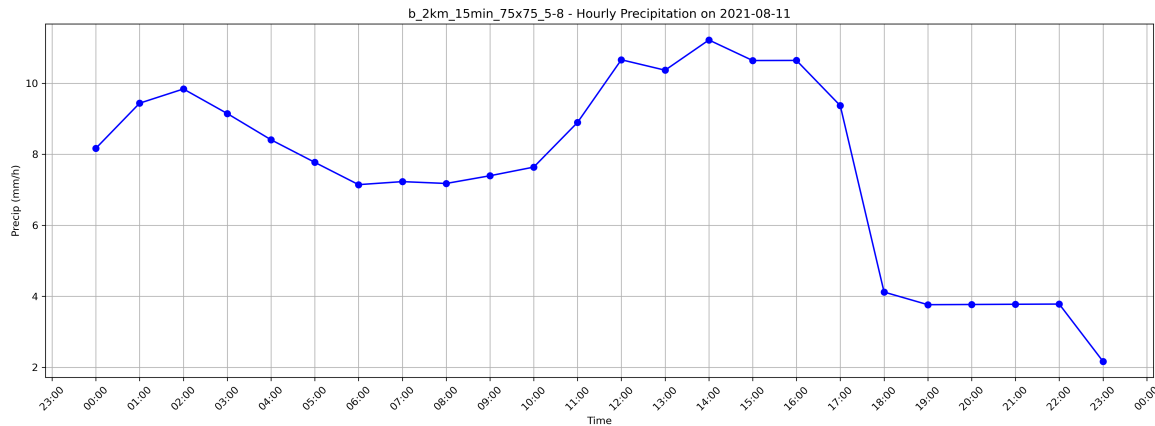


Figure 3.7. Best CP-RegCM Simulation Results - Precipitation Characteristic for 1 Hour.

Figure 3.10 and Figure 3.11 compare the August 2021 RegCM5-simulated maximum precipitation intensities (magenta line) with the regional Intensity–Duration–Frequency (IDF) curves derived for the Bozkurt area. The RegCM5 August maxima exceed the 25-year return period threshold for short durations (1–6 h) and approach or surpass the 50-year level for longer durations (12–24 h). This alignment indicates that the August 2021 rainfall event was statistically rare and consistent with a high-return-period extreme. The shape of the RegCM5 curve suggests sustained heavy rainfall over multiple durations, not only short bursts, which amplifies flood potential in steep, nar-

row catchments like the Ezine Basin. These results agree with observations from TSMS and AFAD, which reported over 400 mm in 48 hours during the event, highlighting that the model captures the magnitude and temporal distribution of the precipitation well. The findings support the classification of the Bozkurt flood as an extreme, high-impact event with characteristics comparable to or exceeding those of rare historical extremes in the region.

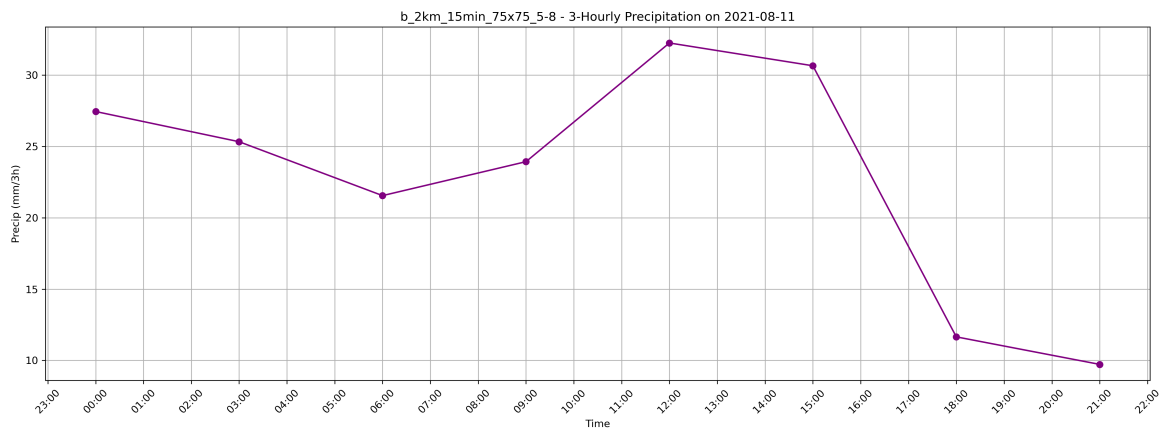


Figure 3.8. Best CP-RegCM Simulation Results - Precipitation Characteristic for 4 Hour.

On the hydrological side, the SWAT model was also tested, and several limitations were observed, especially regarding flash flood representation. Despite using high-resolution sub-basin delineations (approximately 1 km²), hourly weather input, and detailed land use/soil maps derived from ESA WorldCover and HWSD, SWAT was not able to reproduce the rapid rainfall–runoff dynamics observed during the Bozkurt flood. The most notable problem was the delayed response of discharge, it is visualised in Figure 3.16—simulated hydrographs rose too slowly, and peak flow occurred significantly later than the observed flood timing. This mismatch persisted even when model inputs were optimized. SWAT’s internal structure, which is designed to simulate long-term hydrological processes, relies on conceptual routing and a simple unit hydrograph approach. As a result, it struggles with the fast-response behavior of flash floods in small, steep basins like Bozkurt.

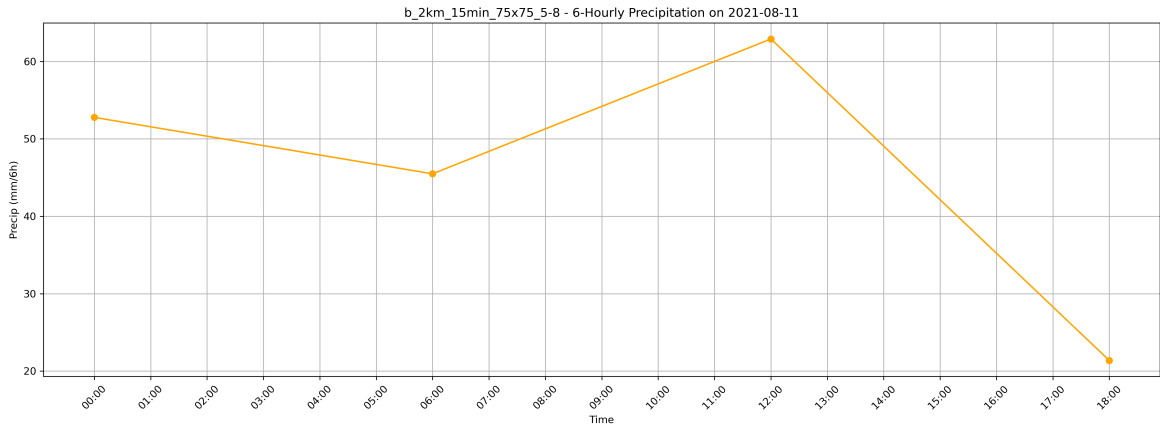


Figure 3.9. Best CP-RegCM Simulation Results - Precipitation Characteristic for 6 Hour.

The most contributing sub-basins (IDs 1, 2, 3, 13) appear to have a significant overlap with urban or semi-urban land cover classes (e.g., ESA code 50), suggesting that impervious surfaces may have accelerated runoff and limited infiltration during the flash flood event. This pattern is consistent with urban flood dynamics and supports the interpretation of rapid runoff response in these critical zones (Figure 3.12, Figure 3.14 and Figure 3.15).

Moreover, while spatial discharge patterns were generally consistent with topography—indicating higher flow accumulation in the upstream regions and around key tributaries—SWAT still smoothed the hydrograph and failed to capture the peak intensity and short lag times. It became clear that SWAT, even under ideal input conditions, lacks the necessary responsiveness to simulate sudden flood waves triggered by short, intense convective rainfall. This limitation aligns with findings in the literature, where SWAT has been shown to perform well for seasonal and long-term flow estimates but not for real-time or extreme event forecasting unless modified or coupled with other routing tools.

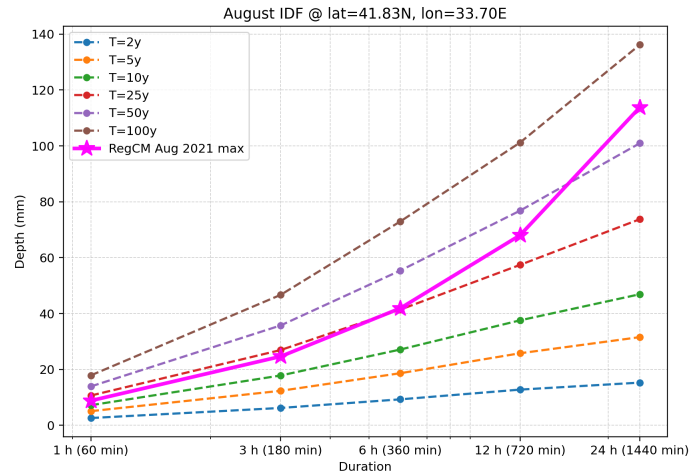


Figure 3.10. August DDF Curve Comparison with Real Data and Best RegCM Ouptur.

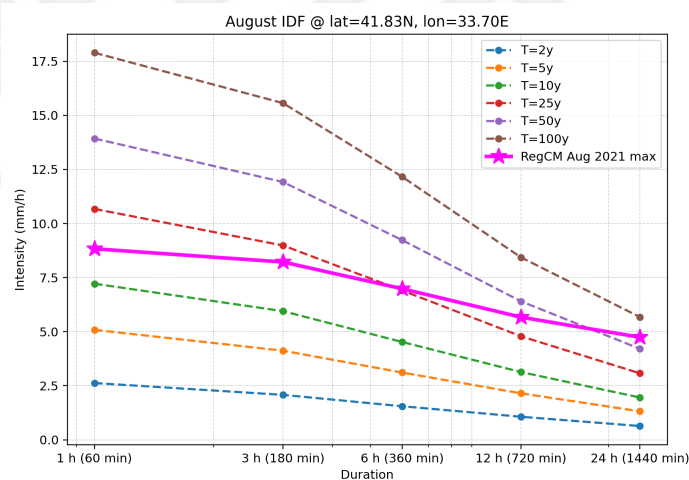


Figure 3.11. August IDF Curve Comparison with Real Data and Best RegCM Ouptur.

In conclusion, SWAT was still useful for identifying discharge hotspots and understanding general runoff patterns across the basin, but it is not suitable as a standalone tool for flash flood timing and peak accuracy. Future work should consider integrating event-based hydrological models or enhancing SWAT with dynamic routing options to better simulate the behavior of flash floods in steep catchments. In contrast, RegCM5 with MOLOCH showed strong capabilities for detecting flood-triggering rainfall events, particularly when high resolution, proper domain placement, short time steps, and

high-frequency outputs were used. However, limitations remain, including precipitation displacement, timing shifts, high computational demand, and technical sensitivities such as RSUB_TOP. For flash flood modeling in complex basins, a combination of detailed atmospheric modeling and specialized hydrological tools is recommended, with attention to both model strengths and known constraints.

In the context of Bozkurt, which is located in the Western Black Sea Region of Turkey, steep topography and short hydrological response times create a high sensitivity to intense, short-duration rainfall. However, based on the model outputs, it was observed that not all runs successfully reproduced such intensity levels within short time windows. In several simulations, the rainfall was either distributed too evenly over longer periods or timing shifted, resulting in values below the accepted thresholds. Therefore, not all simulations could be classified as flash flood scenarios, despite having a convection-permitting setup and realistic spatial patterns.

This evaluation highlights the importance of not only total rainfall but also its timing and concentration. Even when domain placement, microphysics, and resolution are correctly configured, flash flood characteristics may not emerge if the convective core forms too late, too early, or in a displaced area. These results are valuable in identifying where adjustments are needed for better alignment with observed flood-triggering mechanisms.

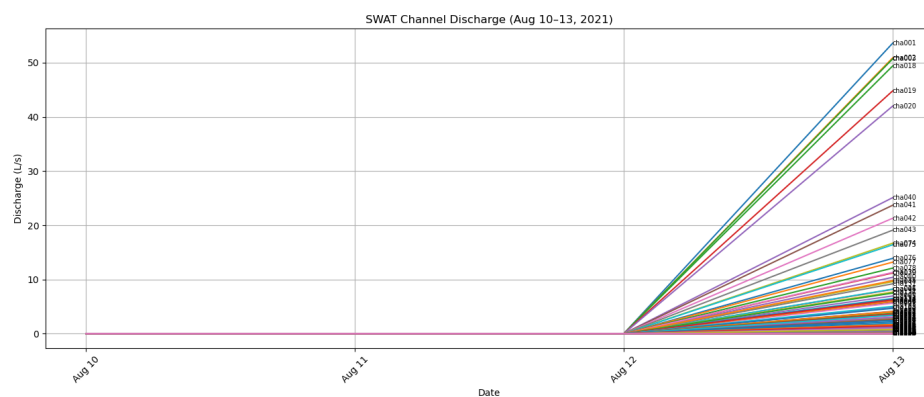


Figure 3.12. SWAT Channel Discharges.

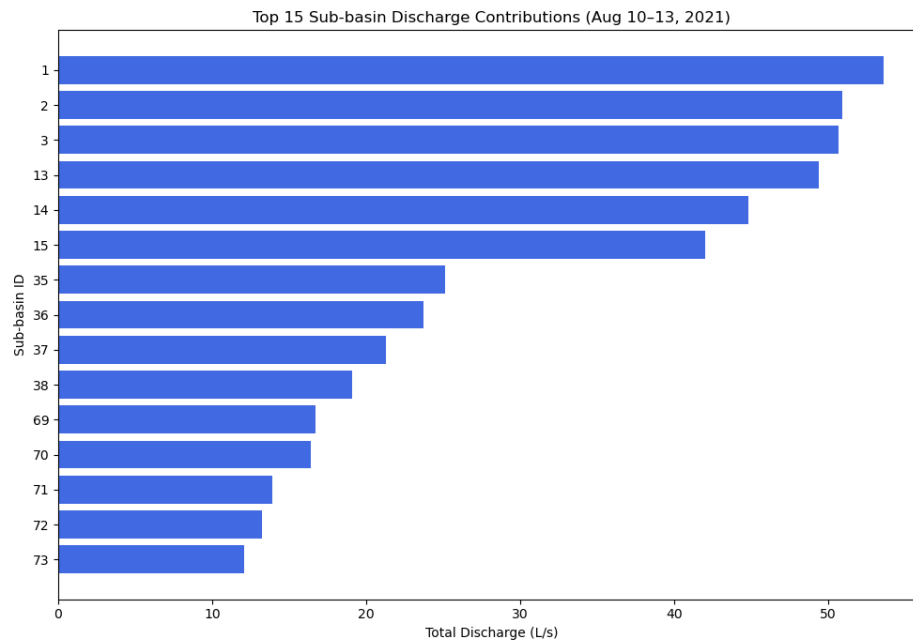


Figure 3.13. SWAT Subbasin Discharge.

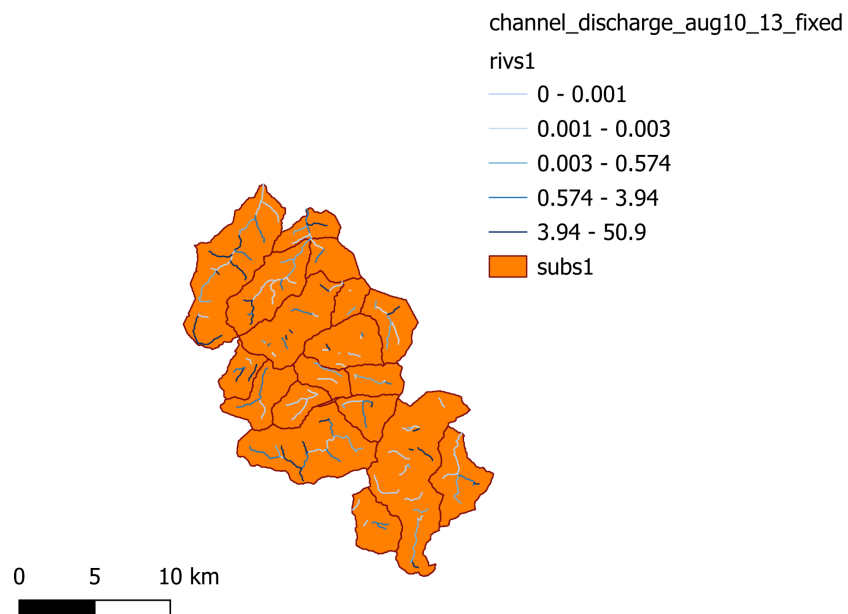


Figure 3.14. SWAT Channel Discharges - Spatial Visualization.

It is important to note that the Bozkurt flood was likely not caused by rainfall intensity alone. Several contributing factors may have amplified the flood's severity and speed. The topography of the region, characterized by steep slopes and a narrow valley, increases surface runoff and limits the floodplain's buffering capacity. In addition, the Ezine Stream, which flows through Bozkurt, had undergone modifications such as narrowing and partial covering. These interventions likely reduced the stream's ability to carry excess water, especially during high-flow conditions. Infrastructure failures, including undersized culverts and blocked bridges, may have caused water to back up and rapidly overflow into urban areas.

Channel Flow and Surface Runoff – Bozkurt

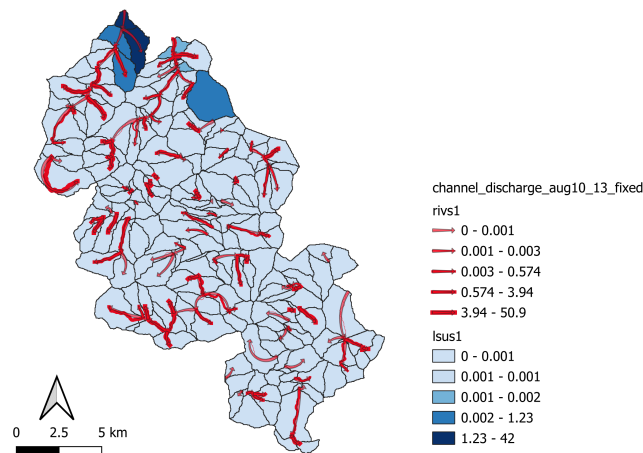


Figure 3.15. SWAT Basin Discharges - Spatial Visualization.

Moreover, urbanization and land use changes in the upstream catchment may have reduced infiltration and accelerated surface flow. Deforestation and increased impervious surfaces contributed to reduced soil storage capacity, further intensifying the runoff. It has also been suggested that debris transport—including logs, mud, and sediment—played a major role by clogging channels and creating temporary blockages, which could have led to sudden, destructive surges when these dams failed.

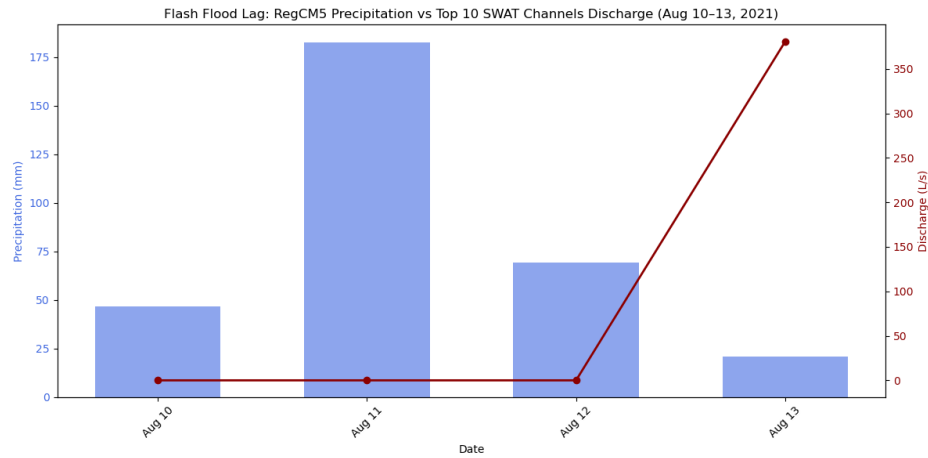


Figure 3.16. SWAT Flood Lag.

Finally, the meteorological conditions present during the August 2021 event were highly favorable for a sustained convective system. Orographic lifting over the Küre Mountains and potential local convergence zones may have prolonged the rainfall period and focused precipitation over the same basin repeatedly. These complex interactions are not always fully captured in regional models, especially if domain setup, lateral forcing, or initial conditions do not allow the convective system to develop in the correct location and time. Therefore, even though some model runs performed reasonably well, the pattern mismatch in others may reflect not only model limitations but also the complexity of the real event, which was likely shaped by a combination of hydrometeorological triggers, topographic constraints, and human-induced vulnerabilities.

4. CONCLUSION

This study explored the integration of high-resolution regional climate data and distributed hydrological modeling to simulate a real flash flood event in Bozkurt, Kastamonu. By combining the non-hydrostatic convection-permitting configuration of RegCM5 with the SWAT hydrological model, the August 2021 flash flood was modeled with increased temporal and spatial accuracy. The use of different high spatio-temporal resolution RegCM output allowed for the representation of short-duration, high-intensity rainfall events, which are critical in flash flood generation.

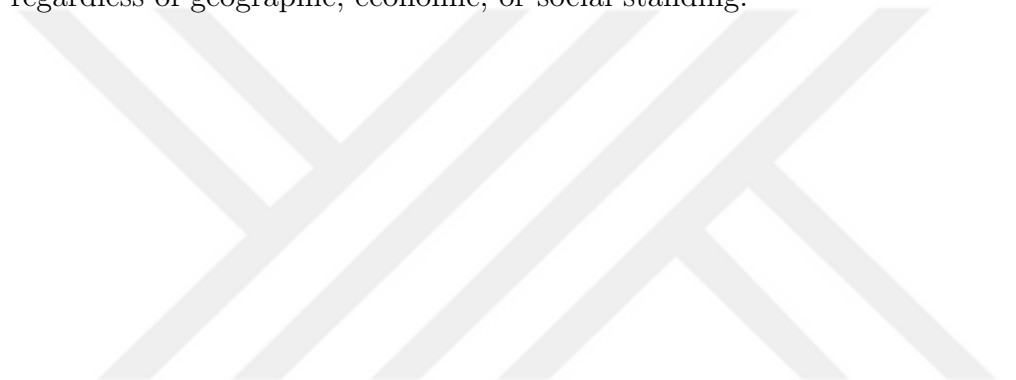
The simulation results indicate that the integrated model framework is effective in identifying vulnerable sub-basins and understanding the runoff response under extreme meteorological conditions. SWAT, when driven by CP-RCM output, reproduced surface runoff dynamics that aligned well with the known impacts of the 2021 flood. This approach contributes to improving local flood risk assessments, especially in topographically complex regions where coarse-scale climate models often fail to capture extreme convective behavior.

Overall, the study emphasizes the importance of multi-model integration for disaster preparedness and urban planning, showing that localized high-resolution modeling is a valuable tool for enhancing early warning systems, infrastructure design, and community resilience to flash floods.

The catastrophic flood event in Bozkurt, Kastamonu exemplifies how climate-related disasters disproportionately affect communities with limited adaptive capacity and delayed early warning. Despite advancements in hydrological modeling and regional climate forecasting, the lack of timely, accessible risk communication systems exacerbates vulnerabilities on the ground.

This study emphasizes that scientific progress—while essential—is not enough on its own. To effectively reduce climate risk, early warning systems, modeling tools, and mitigation strategies must be equitably accessible to all, particularly to those at the frontlines of climate impacts.

Ensuring climate justice means embedding fairness and inclusion into the development and deployment of climate technologies. It calls for a shift from reactive recovery to proactive, people-centered adaptation, where no community is left behind, regardless of geographic, economic, or social standing.



5. FUTURE WORK

While this study presents a promising framework for flash flood simulation using physically based models, several directions remain open for future improvement and extension.

Hourly or sub-hourly hydrological modeling: Although RegCM5 outputs were available at 15-minute intervals, SWAT operates on a daily time step by default. Future work could incorporate modified or custom-coded versions of SWAT, or alternative hydrological models such as MIKE SHE, HEC-HMS, or FLO-2D, which support sub-daily simulation and can better reflect flash flood onset and peak timing.

Multi-event validation: This thesis focused on the August 2021 Bozkurt flood. Expanding the methodology to cover multiple historical events across different seasons or basins would help validate the robustness of the simulation chain under varying initial and boundary conditions.

Climate change scenarios: Current simulations are based on present-day reanalysis data. Future studies could run RegCM5 using global climate model boundary conditions under future emission scenarios (e.g., SSP2-4.5, SSP5-8.5) to assess how flash flood risks may evolve due to climate change in Bozkurt and similar basins.

Real-time flood forecasting: Integrating real-time weather data, radar-based rainfall estimates, and in-situ soil moisture data could support the development of an operational early warning system. Model outputs could be fed into decision-support dashboards for local emergency authorities.

Socioeconomic vulnerability mapping: Future work could integrate the physical flood risk outputs (e.g., surface runoff, FFPI) with socioeconomic layers such as population density, infrastructure exposure, and land use change, enabling compound flood

risk assessments that include both hazard and vulnerability dimensions.

Machine learning and deep learning applications: There is growing potential for applying ML and DL techniques to flash flood modeling. These data-driven approaches can complement traditional hydrological models, especially in regions with limited ground observations. Combining physically based models with AI-enhanced tools could lead to more accurate, faster, and more adaptive flood prediction systems — a critical step toward resilient disaster management in the face of climate extremes.



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APPENDIX A: DATA SOURCES & CODES

All codes used in this study, along with the model run input files, are open-source and available in the associated GitHub repository. The link is provided at the end of the appendix. https://github.com/EceOzen/Bozkurt_Case_Study_Flash_Flood

