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Research Article

Flood Social Vulnerability Assessment: A Case Study of Türkiye

Türkiye Örneği Özelinde Taşkın Sosyal Etkilenebilirlik Analizi

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Abstract

Among all natural disasters, floods are the most frequent and destructive one by far. Assessment of drivers and quantification of flood risk are crucial for humanity preventing its massive consequences. It is required to combine social and biophysical components of the flood risk so that it is comprehensively evaluated. In this study, Social Vulnerability Index, which assesses the adaptability and sensitivity of population to any hazard, were applied in Türkiye. 9 different parameters were used as a vulnerability indicator based on literature review and data availability. 13 cities were identified as highly and very highly vulnerable. Flood frequencies were determined by numbers of flood events occurred among 1960-2021 in each city. Only 3 of 13 cities (Ordu, Kütahya and Sinop) had the highest Flood Social Vulnerability levels as a result of the combination with Flood Frequency Index. The Flood Social Vulnerability Index analysis showed that only the social dimension of the risk is not enough to evaluate risk itself since the biophysical dimension defines the probability of any disaster to happen. The method utilized in this study can be an effective tool for decision-makers to allocate aids to improve flood preparedness over the country.
Keywords: *flood vulnerability, social vulnerability, flood frequency, flood social vulnerability index*

Öz

Doğal afetler düşünüldüğünde, taşkınlar en sık karşılaşılan ve de en fazla hasara sebep olanlar arasında yer almaktadır. Taşkın riskini oluşturan bileşenlerin değerlendirilmesi ve riskin sayısallaştırılması, bu risk gerçekleştiğinde karşılaşılması beklenen büyük boyutlu etkilerden korunmak için önemlidir. Taşkın riskini kapsamlı bir şekilde değerlendirebilmek için riskin sosyal ve biyofiziksel katmanlarının birlikte ele alınması gerekmektedir. Bu çalışmada, toplumun herhangi bir dış baskı faktörüne karşı adaptasyon yeteneğini ve duyarlılığını ölçen Sosyal Etkilenebilirlik Endeksi, tüm Türkiye genelinde il bazında değerlendirilmiştir. Literatür taraması ve veri ulaşılabilirliği göz önüne alınarak 9 farklı etkilenebilirlik parametresi belirlenmiştir. Sosyal Etkilenebilirlik Endeksi analizi sonucunda 13 şehir yüksek ve çok yüksek derecede etkilenebilir olarak nitelendirilmiştir. 1960 ve 2021 yılları arasındaki tarihi taşkınlar il bazında analiz edilmiştir. Sosyal Etkilenebilirlik Analizi ve tarihi taşkınların değerlendirilmesi sonucunda bu 13 şehirden yalnızca 3'ü (Ordu, Kütahya ve Sinop) Taşkın Sosyal Etkilenebilirlik Endeksi'nde en yüksek dereceyi almıştır. Bu Taşkın Sosyal Etkilenebilirlik Endeksi

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analizi sonuçları yalnızca riskin sosyal veya biyofiziksel katmanlarının yeterli olmadığı, riskin kapsamlı şekilde ifade edilebilmesi için bu iki katmanın birlikte değerlendirilmesi gerektiğini ortaya koymuştur. Bu çalışmada uygulanan ve önerilen yöntem karar vericiler için kullanışlı bir metod olmakla beraber tüm Türkiye'deki taşkın hazırlık yetkinliğini arttırmada rol oynayabilecektir.

Anahtar sözcükler: *taşkın etkilenebilirlik, sosyal etkilenebilirlik, taşkın sıklığı, taşkın sosyal etkilenebilirlik analizi*

Introduction

Floods are one of the most frequent and destructive type of natural disaster (Hirabayashi et al., 2013; Tanir et al., 2021). Population increase and economic growth in flood-prone areas are considered the main reasons for the destruction (Rufat & Botzen, 2022). It is estimated that flood frequency and population exposure to flood events are going to increase because of rapid urbanization, deforestation, and climate change (Hirabayashi et al., 2013; Nasiri et al., 2016). The quantification of flood risk is one of the challenges in the process of flood management for decision-makers (Ranger et al., 2011). Therefore, flood risk assessment, which is defined as a methodology to quantitatively assess flood risk, becomes very crucial in managing mitigation and adaptation efforts (Díez-Herrero & Garrote, 2020). Two main components of flood risk have been identified as flood hazard and flood vulnerability (Lugeri et al., 2010; Mohanty et al., 2020; Tascón-González et al., 2020; Tate et. al, 2021). The magnitude of the flood hazard depends on several characteristics of events such as intensity, duration, and timing phase (United Nations International Strategy for Disaster Reduction [UNISDR], 2017). Additionally, the characteristics of the basin such as slope, vegetation, and soil type also determine the severity of flood hazards (Taghavi et al., 2011).

Vulnerability is defined as a "measure of how a system is sensitive, susceptive, and adaptive to any hazard" (Munyai et al., 2019). Flood vulnerability is a quantification of how people, societies, or any kind of system will be affected by any flood events (Munyai et al., 2019; Tanir et al., 2021a; Zahran et al., 2008). By comparing the vulnerability levels of different societies, sensitivity and adaptive capacity of a society to flood hazards are also evaluated (Munyai et al., 2019). According to the literature on vulnerability assessment, the higher socially vulnerable populations leads lower levels of disaster preparedness (Zahran et al., 2008). Knowing the location of the vulnerable population, which are considered as the people that will be affected more than the rest of the population, enable that decision-makers allocate resources more efficiently in flood mitigation efforts and improve the overall flood preparedness level of the society (Chen et al., 2019).

There are numerous studies evaluating the spatial distribution of social vulnerability of people over regions. The most important studies are conducted in United States (Cutter et al., 2003), Southern Italy (Masia et al., 2018), Norway (Holand et al., 2011), and Zimbabwe (Mavhura et al., 2017). In addition, some researchers have studied the combined risk by merging social vulnerability with flood hazard/exposure in Greece (Karagiorgos et al., 2016), Germany (Fekete, 2009), Bangladesh (Hoque et al., 2019), Vila Nova de Gaia/ Portugal (Fernandez et al., 2016), and Hainan Region of China (Yang et al., 2018). To the best of our knowledge, there is no study assessing social vulnerability to floods, by considering both physical and social dimensions of flood risk, over the entire Türkiye. However, Social Vulnerability Index (SOVI) are used in various studies such as fisheries (Gómez Murciano et al., 2021). Also, the vulnerabilities for specific natural hazards in smaller areas are studied in the literature. Duzgun et al. (2011) assessed integrated earthquake vulnerability in Odunpazarı district (Eskişehir), while Yücel and Arun (2010) investigated social vulnerability to earthquake over Avcilar Region in Istanbul. In addition, urban flash flood vulnerability is conducted in Ayamama River, İstanbul to identify adaptation strategies (Reyes-Acevedo et al., 2011).

Therefore, our study aims to quantify both SOVI and Flood Frequency Index (FFI) over Türkiye and combine them to evaluate Flood Socio-Economic Vulnerability Index (FSOVI). By comparing all indexes, locations with higher vulnerability, flood frequency and combination of both of them are highlighted. Identification of those highlighted areas may help decision-makers to allocate resources for improving flood preparedness.

Material and Method

Study Area

Türkiye which covers an area of approximately 780,580 km^2 is located between 36-42 north latitude and 26-45 east longitude. 107 main rivers which have an area of nearly 1500 km^2, drain to Türkiye. The rivers of Kızılırmak, Yeşilırmak, Fırat, Dicle, Aras, Ceyhan, Seyhan, and Çoruh are some of the longest rivers (Akbulut et al., 2022). Total 3973 flood events with different drivers have been recorded in Türkiye since 1960 (General Directorate of State Hydraulic Works [DSİ], 2022). The spatial distribution of those flood events is demonstrated in Figure 7.

Türkiye is divided into 81 cities and 7 geographical regions which contains cities with similar demographics, economic activities, and geographic features. According to the survey of Address Based Population Registration System, 2021, 84,6 million people are living in Türkiye (Turkish Statistical Institute [TUIK], 2022). İstanbul, Ankara, and İzmir are the most populated cities in Türkiye.

Flood impacts are observed almost everywhere in Türkiye. The spatial characteristics of population distribution, socio-economic status, and demographics are non-homogenous over the country. Thus, it is required to assess the vulnerability to flood hazards in the cities.

Methods

Flood socioeconomic vulnerability was assessed by combining the SOVI and FFI (Tanir et al., 2021; Tanir et al., 2021b). While combining them, new index values are determined by considering the value of SOVI and FFI. Both SOVI and FFI were quantified at the city scale in Türkiye. Therefore, combined FSOVI was also evaluated at the city scale.

In our study, SOVI was performed with the hazard of place approach (Cutter et al., 2003; Cutter et al., 2012) which enables researchers to combine biophysical, social, and socioeconomic parameters to evaluate vulnerability levels of geographic locations (Fernandez et al., 2016; Khajehei et al., 2020; Tanir et al., 2021a). A variety of vulnerability parameters have been used on the characteristics of the studied area (Roder et al., 2017).

The parameters used for the definition of overall social vulnerability and their correlations with overall vulnerability are listed in Table 1. The representativeness of vulnerability parameters to the study area, accessibility of data should be considered while defining vulnerability variables for vulnerability assessments (Roder et al., 2017). Therefore, parameter selection for vulnerability definition was made by considering the accessibility of the data for each province and the frequency of appearance of those parameters in the relevant literature for this study. All data were obtained from dataset 2020 of TUIK.

Populations with a higher portion of females, elder people, and illiterate people are more likely to be affected by any hazard (Bolin & Bolton, 1986; Chakraborty et al., 2020; Cutter et al., 2003; Fernandez et al., 2016; Khajehei et al., 2020; Medina et al., 2020; Roncancio & Nardocci, 2016; St. Cyr, 2005; Tanir et al., 2021a). In addition, the less accessible health service reduces the adaptive capacity of a population to any hazard (Santos et al., 2018; Zhang & Huang, 2013). Also, more densely populated regions tend to have higher vulnerability levels (Mansur et al., 2016; Zahran et al., 2008)

Table 1

Social Vulnerability Parameters and Correlation with Vulnerability

Parameters	Correlation with Vulnerability
Number of doctors per thousand People	Negative
Percentage of Female	Positive
Percentage of Elder Dependency	Positive
Percentage of Illiterate People	Positive
Average Household Size	Positive
Numbers of Hospital	Negative
Gross Domestic Product (GSYH)	Negative
Population Density	Positive
Flood Protection	Negative

Principal Component Analysis (PCA), which is a well-known factor analysis method to aim reduce the number of parameters by optimizing the storage of information in the dataset (Absonet al., 2012; Chakraborty et al., 2020; Cutter & Finch, 2018; Khajehei et al., 2020; Mohanty et al., 2020; Tanir et al., 2021a), was applied in this study. As the PCA procedure was used to decrease the number of parameters and combine them with weights without losing too much information (Kong et al., 2017).

Before using PCA procedure, correlation and their trends depending on overall vulnerability were analyzed. The normalization procedure was applied so that the data with different units could be used in the analysis. The incommensurability problem of using data with different units has been solved by that linear transformation which maintains the correlation structure of original data (Abson et al., 2012; Kong et al., 2017). There are several normalization methods such as maximum-minimum normalization, z-score normalization, distance to target, and ranking-based normalization (Moreira et al., 2021). However, according to Moreira et al. (2021), there is a low sensitivity regarding the normalization methods in flood vulnerability assessments. One of the most widely used method: Maximum-minimum normalization method (Chakraborty et al., 2020; Tanir et al., 2021a) was applied in this study. This method compresses the data between the maximum and minimum values by following the equation below (Eqn.1).

$$P_{normalized}= (P_{actual}-P_{min})/(P_{maximum}-P_{minimum}) \qquad \text{(Eqn. 1)}$$

After the application of this method, the highest value in the dataset was represented as 1 while the lowest was 0.

There are some statistical tests, such as Bartlett's Test of Sphericity and Kaiser-Meyer Olkin's (KMO) measure of sampling adequacy, that are prior to PCA procedure to check whether data is appropriate for PCA or not (Chakraborty et al., 2020; Gu et al., 2018; Monterroso et al., 2014). After conducting normalization procedure, both of the tests were applied to the dataset and these tests were successful. Then, the PCA procedure was applied. The positively and negatively correlated parameters with social vulnerability were combined individually (Eqn. 2, Eqn. 3, and Eqn. 4). Visual assessment method by the scree plot was utilized to determine the number of principal components (Chakraborty et al., 2020). The number of components is needed to be optimized to explain maximum information by using fewer principal components (Tanir et al., 2021a).

$$SOVI_{(+)} = (\text{Weight of } PCA_{1+} * PCA_{1+}) + \ldots (\text{Weight of } PCA_{5+} * PCA5_{+}) \quad \text{(Eqn. 2)}$$

$$SOVI_{(-)} = (\text{Weight of } PCA_{1-} * PCA_{1-}) + \ldots (\text{Weight of } PCA_{5-} * PCA_{5-}) \quad \text{(Eqn. 3)}$$

$$\text{Overall } SOVI = SOVI_{(+)} - SOVI_{(-)} \quad \text{(Eqn. 4)}$$

After calculating all negative and positive SOVI values, the maximum-minimum normalization process was reapplied for being able to compare all results. As a result, all cities had a vulnerability index value between 0 and 1. The breakdown and distribution of those vulnerability values are demonstrated with the Natural Jenks method by using ArcGIS.

Historical flood data from the General Directorate of State Hydraulic Works (DSI) were used for the flood frequency analysis. The number of historical floods experienced among 1960-2021 were subjected to a normalization procedure so that the results of SOVI and FFI could be combined. Similar to SOVI, the Natural Jenks method was utilized in order to demonstrate spatial distribution of flood hazards on a map. Therefore, each city had a vulnerability value as well as a flood frequency value which defines the likelihood of flood hazard to happen.

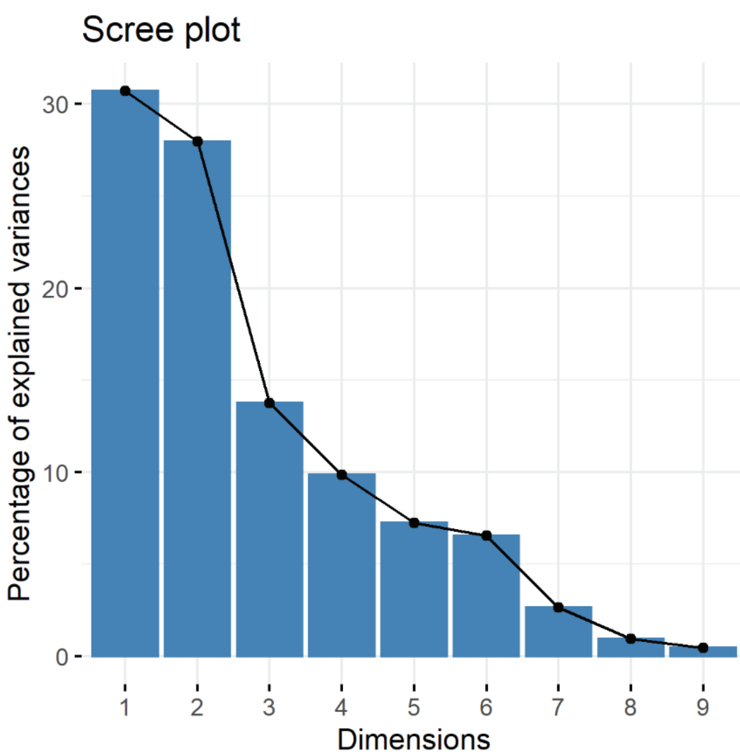
Then, normalized SOVI and FFI values were merged together to define Flood Social Vulnerability Index (FSOVI). Very low and low SOVI and FFI values were expressed as low FSOVI values. The ones at medium level in both indexes were also indicated as a medium in FSOVI while high and very high ones were considered as high value for FSOVI. Finally, all results were interpreted spatially.

Results

89% of the total information of the database was explained with 5 principal components by using visual assessment of the scree plot after PCA. It is stated that saving at least 70% of total information is acceptable in studies that use PCA as factor analysis (Fekete, 2009; Ganguly et al., 2019; Roder et al., 2017; Tanir et al., 2021a). Thus, amount of information stored in principal components is consistent with the literature. As seen in Figure 1, the percentage of explained variances is significantly higher in the first two dimensions. The percentage of explained variances falls below 10% after the 4th dimension.

Figure 1

Scree Plot (Percentage of Explained Variances)



Correlation analyses were conducted before PCA. Figure 2 illustrates that which parameters are correlated with each other and how they are correlated. The color states relation of those parameters with each other. For instance, household size and elder dependency are negatively and highly correlated (Figure 2). In addition, Gross

Domestic Product (GDP) and population density are positively correlated. Highly correlated parameters were reviewed separately in order to observe a relation between each other in Figure 3 and Figure 4.

As two of the highly correlated parameters, the relationship between household size and elder dependency is demonstrated in Figure 3. A major negative correlation is found between those variables.

Figure 2

Correlation of Vulnerability Parameters with Each Other

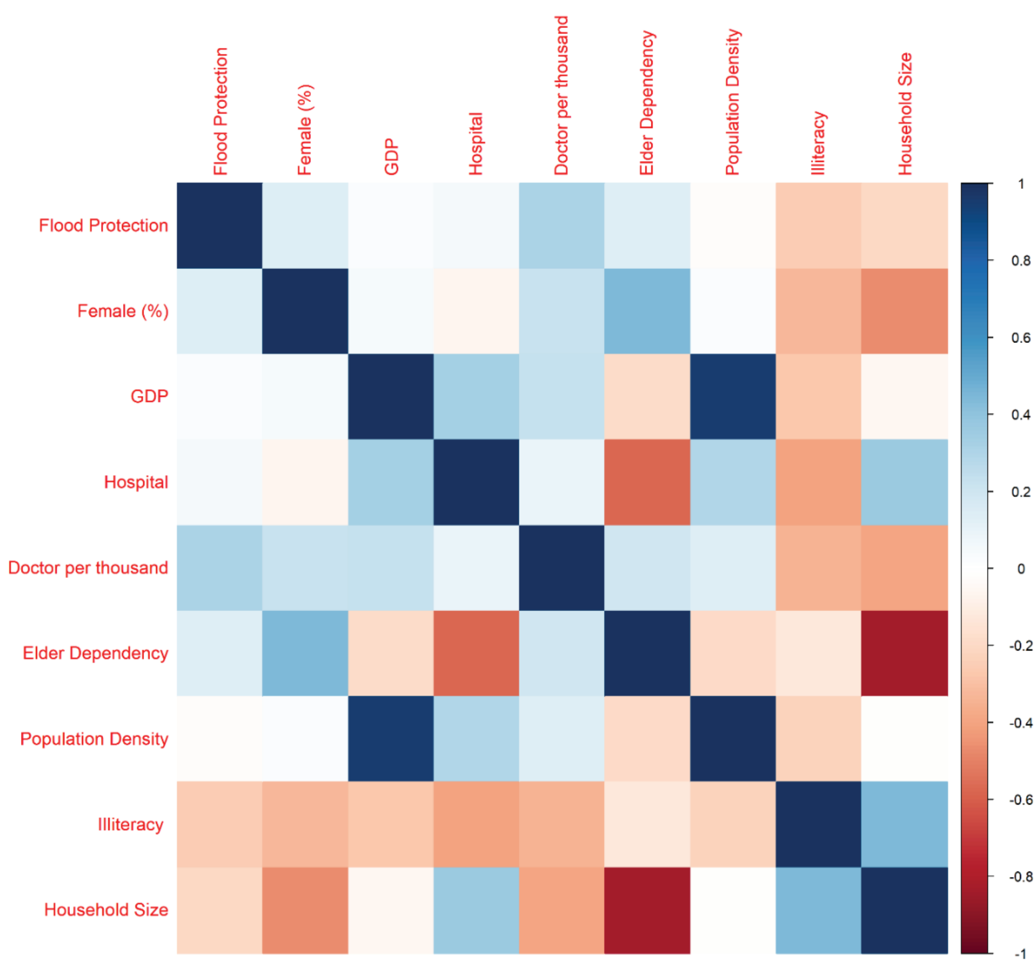


Figure 3

Correlation between Household Size and Elder Dependency

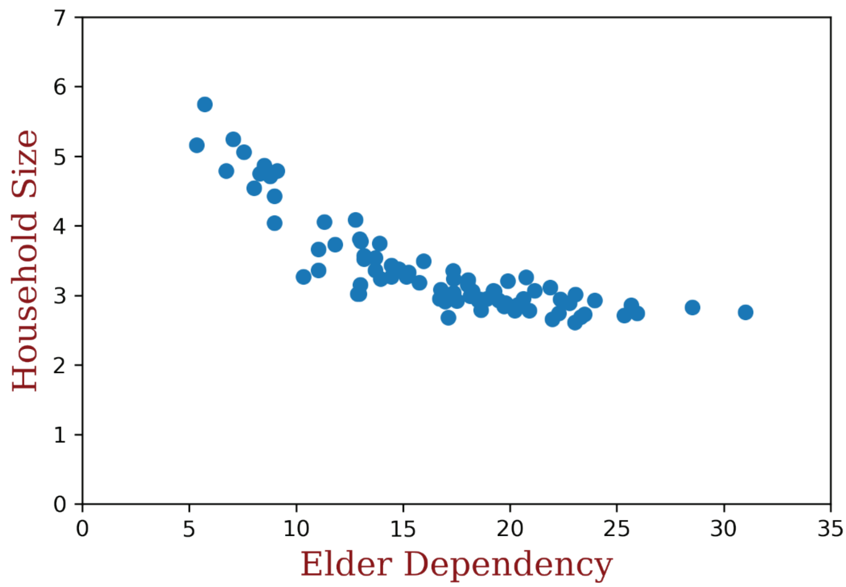
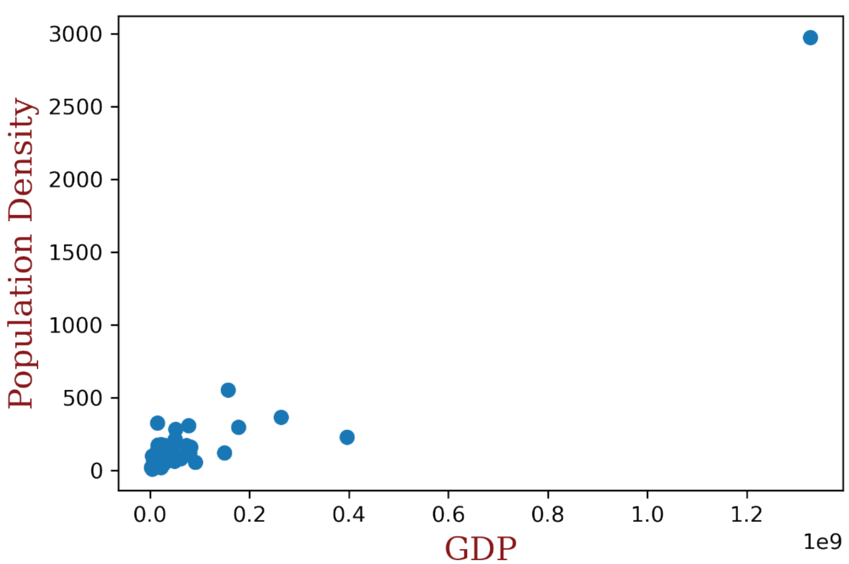


Figure 4

Correlation between Population Density and GDP



Unlike the correlation between household size and elder dependency, the correlation between the population density and GDP is strongly positive (Figure 4). It can be seen that one data point is separated from the rest of the distribution. That data point indicates Istanbul, which is the most crowded city with the highest GDP by far, was not considered as an outlier.

Figure 5 indicates that which parameters have more contribution to the expression of which dimension. The size of the circle shows how each parameter correlated are, while the color states relation of those parameters with each other. For instance, elder dependency, percentage of female population, and household size are the main parameters that explain dimension 1, while GDP and population density contribute more for dimension 2. For the rest of the dimensions, the contribution of parameters to them is distributed more homogeneously.

Figure 5

Correlation of Parameters for Dimensions

Each city was numbered based on the car number plates to facilitate interpretation of the spatial distribution of the SOVI results (Table 2).

Table 2

Car Number Plates of Cities in Türkiye

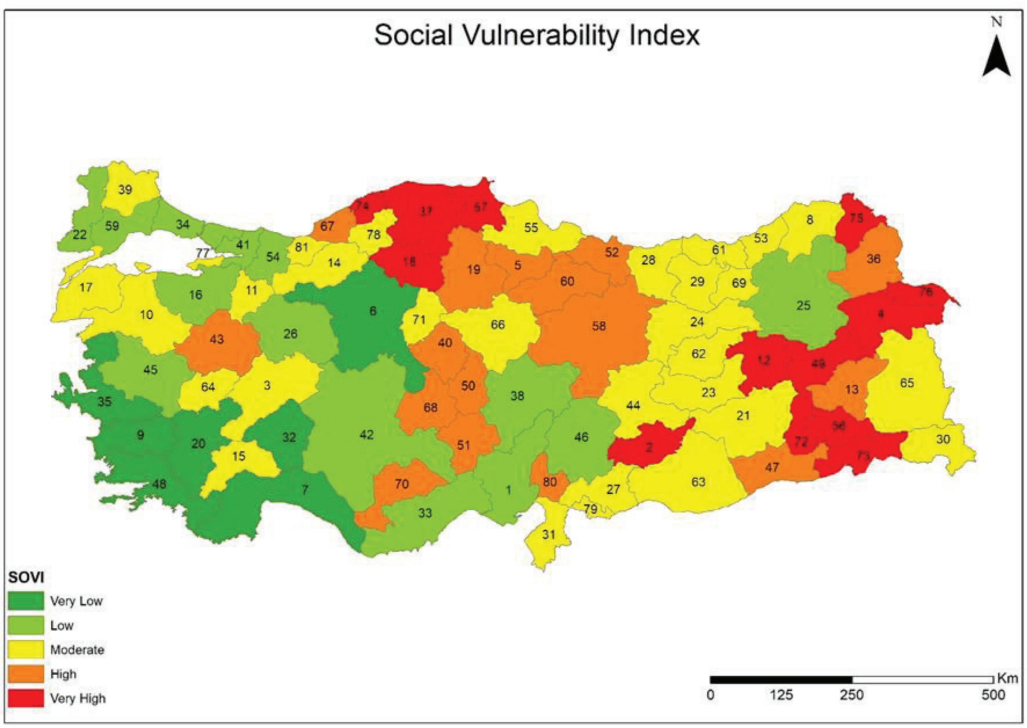
City	No:	City	No	City	No	City	No
Adana	1	Diyarbakır	21	Kocaeli	41	Trabzon	61
Adıyaman	2	Edirne	22	Konya	42	Tunceli	62
Afyon	3	Elazığ	23	Kütahya	43	Urfa	63
Ağrı	4	Erzincan	24	Malatya	44	Uşak	64
Amasya	5	Erzurum	25	Manisa	45	Van	65
Ankara	6	Eskişehir	26	Maraş	46	Yozgat	66
Antalya	7	Gaziantep	27	Mardin	47	Zonguldak	67
Artvin	8	Giresun	28	Muğla	48	Aksaray	68
Aydın	9	Gümüşhane	29	Muş	49	Bayburt	69
Balıkesir	10	Hakkari	30	Nevşehir	50	Karaman	70
Bilecik	11	Hatay	31	Niğde	51	Kırıkkale	71
Bingöl	12	Isparta	32	Ordu	52	Batman	72
Bitlis	13	Mersin	33	Rize	53	Şırnak	73
Bolu	14	İstanbul	34	Sakarya	54	Bartın	74
Burdur	15	İzmir	35	Samsun	55	Ardahan	75
Bursa	16	Kars	36	Siirt	56	Iğdır	76
Çanakkale	17	Kastamonu	37	Sinop	57	Yalova	77
Çankırı	18	Kayseri	38	Sivas	58	Karabük	78
Çorum	19	Kırklareli	39	Tekirdağ	59	Kilis	79
Denizli	20	Kırşehir	40	Tokat	60	Osmaniye	80
						Düzce	81

The spatial distribution of SOVI (Figure 6) demonstrated that 13 cities have a very high vulnerability level among all cities in Türkiye. It was determined that Ağrı (4), Adıyaman (2), Ardahan (75), Bartın (74), Batman (72), Bingöl (12), Çankırı (18), Iğdır (76), Kastamonu (37), Muş (49), Siirt (56), Sinop (57), and Şırnak (73) have the most vulnerable population in Türkiye. Bartın (74), Kastamonu (37), and Sinop (57) are socially more vulnerable due to having high proportion of elder dependency and female in their population, while high percentage of illiteracy and low health service quality are the main reasons for high vulnerability in Ağrı (4), Ardahan (75), Çankırı (18), Iğdır (76) and Muş (49). Batman (72) and Bingöl (12) are two cities with the lowest GDP among all cities.

The cities in the western part have less vulnerable population than the other cities in the middle, northern, and eastern parts of the country. It is determined that İzmir (35) was the least vulnerable city while Sinop (57) was the most vulnerable city in the country.

Figure 6

Spatial Distribution of Social Vulnerability Index in Türkiye



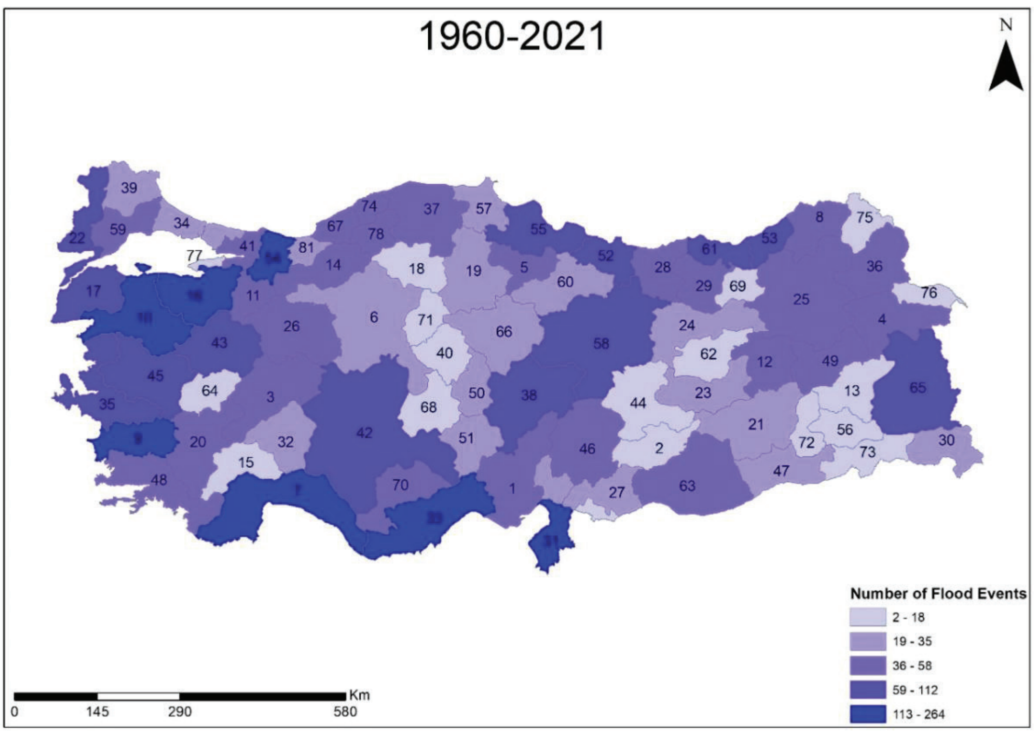
Flood Frequency Analysis

The spatial distribution of flood disasters in Turkey in 61 years from 1960 to 2021 was represented in Figure 7. Natural Jenks method was applied to dataset to identify distribution of flood disasters in Türkiye. As a result, the cities with recorded among 113-264 historical flood events were characterized as high flood frequency while 2-18 events were low flood frequency. Antalya (7), Aydın (9), Balıkesir (10), Bursa (16), Hatay (31), Mersin (33), and Sakarya (54) have experienced more flood events than the other cities in Türkiye. The numbers of flood events in these cities were between the numbers of 113-264. The highest number of flood events was observed in Balıkesir with 264 events.

The spatial distribution of flood disasters indicated that the cities located in west and south side of the country have experienced more floods than its middle, eastern and north-western parts.

Figure 7

Spatial Distribution of Flood Disasters in Türkiye



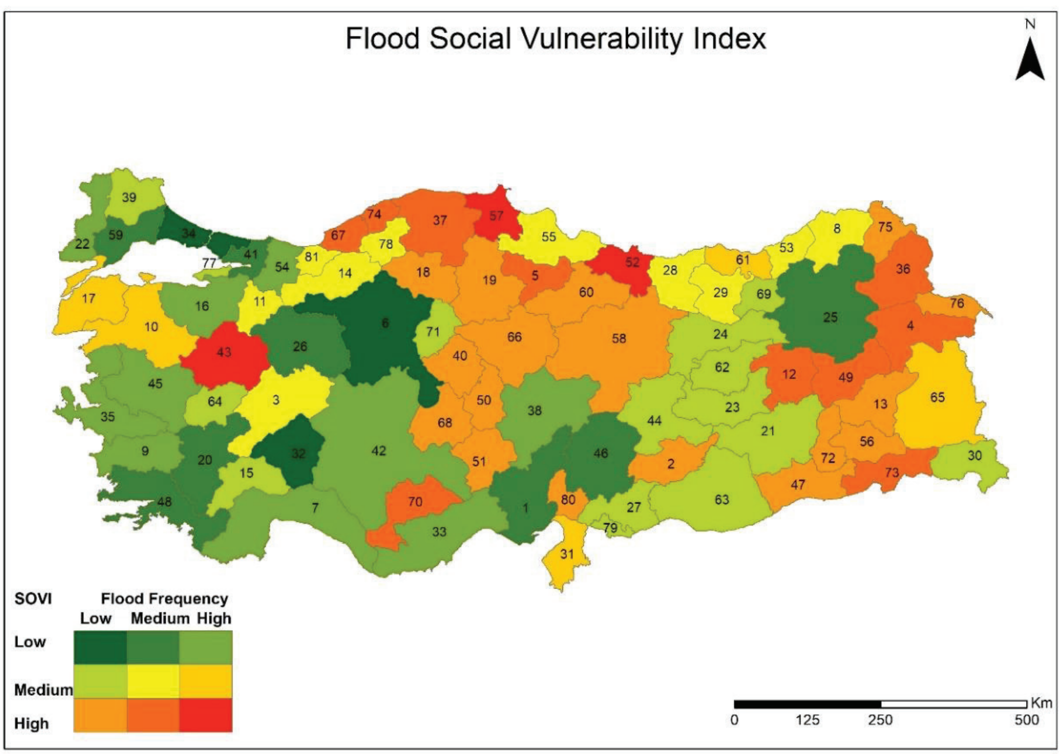
Flood Social Vulnerability Index (FSOVI)

Figure 8 displays the spatial distribution of the FSOVI. Kütahya (43), Ordu (52), and Sinop (57) have the highest FSOVI value among all cities. The cities in the western part of the country are generally less flood socially vulnerable compared to the eastern and middle part of the country since their social vulnerability levels are very low, low, and medium mostly. In addition, the cities located in the northern part of the country were more vulnerable than the southern part of Türkiye. There were highly vulnerable cities [Aksaray (68), Çankırı (18), Çorum (19), Kırşehir (40), Nevşehir (50), Sivas (58), Tokat (60), and Yozgat (66)] in the middle part of the country due to high SOVI values. Ankara (6), Isparta (32), and İstanbul (34) had the lowest FSOVI values due to their low SOVI and FFI values.

Some cities had high flood frequency but low SOVI values such as Antalya (7), Aydın (9), Balıkesir (10), Bursa (16), Hatay (31), Mersin (33), Sakarya (54), and Samsun (55). In contrast to those cities, Adıyaman (2), Ardahan (75), Çankırı (18), Iğdır (76), and Siirt (56) had low flood frequency and high SOVI values due to low GDP and higher female population. As a result, among those with high SOVI and flood frequency, the total FSOVI values are lower for the cases which one of the index is identified as low.

Figure 8

Spatial Distribution of Flood Social Vulnerability Index



Discussion and Conclusion

In the similar study conducted in entire Türkiye for assessing drought vulnerability, the spatial distribution of social vulnerability of its population indicated that Adana (1), Adıyaman (2), Ağrı (4), Ankara (6), Antalya (7), Batman (72), Diyarbakır (21), Gaziantep (27), Hakkari (30), Hatay (31), İstanbul (34), Konya (41), Kahramanmaraş (46), Mardin (47), Muş (49), Niğde (51), Şanlıurfa (63), Şırnak (73), and Van (65) are the cities with the highest social vulnerability (Türkeş, 2017). The results on the spatial distribution of SOVI in the research are partially consistent with our study. Adıyaman (2), Batman (72), Muş (49), and Şırnak (73) were determined as highly socially vulnerable cities in both studies. However, there are some inconsistencies between the results. For instance, Ankara (6) and İzmir (35) were evaluated as having a highly vulnerable population in the study of Türkeş (2017), while they were identified as the least vulnerable cities in this study. This difference between the two studies may be due to the utilization of different vulnerability parameters. In addition, the most recent available data was used in this study compared to of the data in his study (Türkeş, 2017).

This study aimed to assess flood social vulnerability over Türkiye by combining flood frequency and social vulnerability indexes. There are plenty of vulnerability parameters in the literature, but only 9 of them were used in this study due to data availability. Historical flood records among 1960-2021 were examined to assess flood frequency. Both social vulnerability and flood frequency indexes were normalized by the maximum-minimum standardization procedure to solve the incommensurability problem. Then, all indexes were displayed spatially so that highly vulnerable areas to flood disasters were mapped out. This study enabled decision-makers to identify vulnerable populations to flood in Türkiye. The resources may be allocated to improve flood preparedness of vulnerable population with the light of this information. The methodology implemented in this study can be a reference tool for other countries as well. However, specific data assessment needs to be conducted to identify most suitable vulnerability parameters for SOVI.

The spatial distribution of SOVI indicated that Adıyaman (2), Ağrı (4), Ardahan (75), Bartın (74), Batman (72), Bingöl (12), Çankırı (18), Iğdır (76), Kastamonu (37), Muş (49), Siirt (56), Sinop (57), and Şırnak (73) provinces were evaluated as having very highly vulnerable population. In addition, the western part of the country was claimed as less vulnerable compared to other parts of Türkiye. According to the flood frequency analysis, Antalya (7), Aydın (9), Balıkesir (10), Bursa (16), Hatay (31), Mersin (33), and Sakarya (54) had the highest flood frequency. When both of two indexes: FSOVI and SOVI were combined, we recorded that Kütahya (43), Ordu (52), and Sinop (57) were three of cities having the highest value on FSOVI.

Information on spatial distribution of flood is crucial for flood management and emergency response. It will also be a reference tool for decision-makers to allocate resources for flood preparedness. This reference tool can be used to prioritize local disaster response strategies as well. In addition, the methodology can be applied to any other country or Türkiye for watershed-scale as well.

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Extended Turkish Abstract
(Genişletilmiş Türkçe Özet)

Türkiye Örneği Özelinde Taşkın Sosyal Etkilenebilirlik Analizi

Doğal afetler düşünüldüğünde, taşkınlar en sık karşılaşılan ve de en fazla hasara sebep olanlar arasında yer almaktadır. Taşkın riskini oluşturan bileşenlerin değerlendirilmesi ve riskin sayısallaştırılması, bu risk gerçekleştiğinde karşılaşılması beklenen büyük boyutlu etkilerden korunmak için önemlidir. Taşkın riskini kapsamlı bir şekilde değerlendirebilmek için riskin sosyal ve biyofiziksel katmanlarının birlikte ele alınması gerekmektedir. Bu noktada iki farklı katmanı birlikte inceleyip mekânsal bir değerlendirme yoluyla riski ifade edebilen Sosyal Etkilenebilirlik Analizleri kullanılmaktadır.

Bu çalışmada, toplumun herhangi bir dış baskı faktörüne karşı adaptasyon yeteneğini ve duyarlılığını ölçen Sosyal Etkilenebilirlik Endeksi, tüm Türkiye özelinde il bazında değerlendirilmiştir. Sosyal Etkilenebilirlik Analizi dünya literatüründe deprem, kuraklık, taşkın, iklim değişikliği gibi afetlere karşı toplumun kırılganlıklarını ölçmek için yaygın bir şekilde kullanılmaktadır. Daha öncesinde Amerika, Norveç, Güney İtalya, Bangladeş gibi ülkelerde yapılan çalışmalar incelenmiş, veri ulaşılabilirliği de göz önüne alınarak 9 farklı etkilenebilirlik parametresi Türkiye özelinde belirlenmiştir. Bunlar 1000 kişiye düşen hekim sayısı, popülasyondaki kadın oranı, toplam yaş bağlılık oranı (%), okuma yazma bilmeyen sayısı, ortalama hanehalkı büyüklüğü, hastahane sayısı, Gayri Safi Yurtiçi Hâsıla (GSYH bin TL), taşkın koruma tesisinin varlığı ve nüfus yoğunluğudur. Tüm veriler Türkiye İstatistik Kurumu (TÜİK) veritabanından elde edilmiştir. Birbirinden farklı birimlere sahip olan etkilenebilirlik parametrelerini Temel Bileşen Analizi yöntemiyle birleştirebilmek için maksimum-minimum normalizasyonu prosedürü uygulanmıştır. Temel Bileşen Analizi, temelde çok boyutlu bir verisetinin dağılımın anlamının korunacağı şekilde daha düşük boyutlu bir veri setine indirgenmesini sağlayan bir analiz çeşididir. Bu analiz yapılmadan önce bahsekonu verisetinin analize uygunluğunu değerlendirme olanağı veren Bartlett's Test of Sphericity and Kaiser-Meyer Olkin's measure of sampling adequacy testleri verisetine uygulanmış ve test sonuçları Temel Bileşen Analizi prosedürünün uygulanmasında herhangi bir sorun olmadığını göstermiştir. Bu testlerden sonra etkilenebilirliği arttıran parametreler ve azaltan parametreler ayrı ayrı hesaplanıp daha sonra birleştirilmiştir. Bununla birlikte her bir şehir 0 ila 1 arasında bir etkilenebilirlik değeriyle ifade edilmiştir. Fakat Türkiye genelinde yapılan ve kuraklığa etkilenebilirliği analiz eden diğer bir çalışmada (Türkeş 2017) İzmir ve Ankara çok yüksek etkilenebilirlik derecesine sahip olarak ifade edilmişken, bu çalışmada en düşük etkilenebilirlik seviyesine sahip olarak belirlenmiştir. Bunun sebebinin ise her iki çalışmada kullanılan etkilenebilirlik parametrelerinin farklı olmasından kaynaklandığı düşünülmektedir. Ayrıca, 2017 yılında gerçekleştirilen çalışmadaki verilerin bu çalışmadaki veriler kadar güncel olmaması nedeniyle böyle bir farkın ortaya çıkmış olabileceği öngörülmüştür. Ayrıca bu çalışmada kullanılan etkilenebilirlik parametreleri ayrı ayrı incelendiğinde de Ankara ve İzmir'in GSYH, 1000 kişiye düşen hekim sayısı ve taşkın tesisi sayılarının tüm verisetindeki en yüksek değerlere sahip olduğu görülmektedir.

Sosyal Etkilenebilirlik Endeksi analizi sonucunda Adıyaman, Ağrı, Ardahan, Bartın, Batman, Bingöl, Çankırı, Iğdır, Kastamonu, Muş, Siirt, Sinop ve Şırnak olmak üzere 13 şehir çok yüksek derecede etkilenebilir olarak nitelendirilmiştir. Sinop, Bartın, Kastamonu illerinde yüksek yaşlı bağımlılık ve kadın popülasyonu oranı ve düşük taşkın tesisi sayısı, Ardahan, Ağrı, Çankırı, Iğdır, Muş illerinde yüksek okuma yazma bilmeyen nüfus oranı ve düşük doktor ve hastane sayısı, Batman, Bingöl illerinde ise düşük Gayrisafi Yurtiçi Hasıla (GSYİH) oranı yüksek etkilenebilirlik oranına sahip olma nedenleridir.

Türkiye genelinde yapılan bir başka çalışmada (Türkeş 2017) hesaplanan Sosyal Etkilenebilirlik Endeksi'nin ülke genelindeki dağılımının bu çalışmayla tam olarak uyumlu olmadığı belirlenmiştir. Şırnak, Batman, Muş ve Adıyaman şehirleri her iki çalışmada da en yüksek etkilenebilirlik seviyesine sahip olmuştur. İzmir ise Sosyal Etkilenebilirlik Endeksine göre Türkiye'de etkilenebilirlik değerininin en düşük olduğu il olarak belirlenmiştir. İzmir ilinin bu değere sahip olmasında taşkın tesis sayısının ve 1000 kişiye düşen hekim sayısının fazlalığı ile üçüncü en yüksek GSYİH değerine sahip olmasının etkili olduğu tespit edilmiştir.

Taşkın riskinin biyofiziksel katmanı ise tarihi taşkın sayılarıyla tanımlanmıştır. 1960 ve 2021 yılları arasındaki tarihi taşkınlar il bazında analiz edilmiştir. Balıkesir ili 1960 yılından beri kaydedilen 264 taşkın olayı ile Türkiye genelinde en fazla sayıda taşkına maruz kalmış il olmuştur. Sosyal Etkilenebilirlik Analizi ve tarihi taşkınların değerlendirilmesi sonucunda bu 13 şehirden yalnızca Sinop, Kütahya ve Ordu Taşkın Sosyal Etkilenebilirlik Endeksi'nde en yüksek dereceyi almıştır. Balıkesir ili ise orta derecede sosyal etkilenebilirlik değerine sahip olduğu için Taşkın Sosyal Etkilenebilirlik derecesinde düşük bir değere sahip olmuştur. En fazla taşkına maruz kalmış il olan Balıkesir, daha az derecede sosyal etkilenebilir bir popülasyona sahip olduğu için düşük bir risk değerine sahiptir. Taşkın Sosyal Etkilenebilirlik Endeksi analizi sonuçları yalnızca riskin sosyal veya biyofiziksel katmanlarının yeterli olmadığı, riskin kapsamlı şekilde ifade edilebilmesi için bu iki katmanın birlikte değerlendirilmesi gerektiğini ortaya koymuştur. Bu çalışmada uygulanan ve önerilen yöntem karar vericiler için kullanışlı bir metot olmakla beraber tüm Türkiye'de taşkın hazırlık yetkinliğini arttırmada rol oynayabilecektir. Taşkın durumlarında ülkedeki toplam riski ifade eden bu sonuçlar, kapasite geliştirmek için kaynak dağıtımının yapılması hususunda karar vericilere altlık olacaktır. Bu çalışmada uygulanan yöntem ülkede daha küçük ölçeklerde daha detaylı olarak çalışılarak bölgesel taşkın risklerini belirlemede kullanılabilir. Ayrıca, başka ülkelerde ülke çapında yürütülecek çalışmalar içinde metodolojik bir referans olarak kullanılabilir.