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Maximum entropy model-based spatial sinkhole occurrence prediction in Karapınar, Turkey

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Abstract

Sinkholes in Karapınar and their rapidly increasing occurrence rate are considered one of the main hazards that threaten arable lands and human life. The sudden occurrence and unavoidable characteristics of sinkholes make them more dangerous and challenging to avoid. More than 300 sinkholes have been recorded in the Karapınar region of Konya province in Turkey. There are intensive agricultural activities in the region, and therefore over 60,000 water wells are used to meet the demand. Thus, drought, the effects of climate change and decreasing precipitation rate reveal stress on sinkhole occurrence due to the geological structure of the region and its high tendency to sinkholes since ancient times due to its volcanic history.

The primary purpose of this study is to predict possible sinkhole occurrence probabilities in Konya, Karapınar region based on historical occurrences and to report to the authorities to raise awareness about this problem. The Maximum Entropy (MaxEnt) model is applied for sinkhole susceptibility mapping by evaluating 17 variables affecting sinkhole occurrence in meteorological, topographic, environmental, and geological aspects. The results indicated that 458.52 km^2 (2.48%) of the study area is highly susceptible to sinkholes. 100 sinkholes were assigned as sample data, and 45 sinkholes were set as test data for the MaxEnt model. The AUC values of training data with 0.978 and test data with 0.963 were calculated where a good correlation was provided. The variables Annual Mean Temperature, Precipitation Seasonality (Coefficient of Variation) Geology, and precipitation, which are mostly responsible for sinkhole formations, have been calculated.

Keywords: Geographical information systems; karstic formations; maxent; sinkholes; susceptibility mapping

1. Introduction

In recent years, sinkholes have been considered a natural hazard that may cause significant damage to the environment. Since it is challenging to detect underground structures (groundwater, natural caves, etc.) and sudden occurrence characteristics, determining the exact location of sinkholes is very hard unless a collapse or deformation is observed on earth. Sinkholes are closed subsidence areas formed by surface dissolution of bedrock that dissolve in karst (Miao *et al*., 2013). Karst rock areas are generally vulnerable to sinkholes and range from a few meters to hundreds of meters.

The main causes of sinkhole formation can be divided into lithological, hydrogeological, tectonic, and climatological groups. In addition, natural factors anthropogenic reasons also trigger the occurrence of sinkholes, such as urbanization, agricultural activities, and irrigation. Decayed organic matters, rich in organic and carbonic acids, accelerate the dissolution of carbonate rocks naturally. Vibration, water demand, agriculture, and urbanization on limestone accelerate the formation of sinkholes anthropogenically (Bayari *et al*., 2009). Volcanic history and karstic formations have made the region vulnerable to sinkholes since ancient times, and excessive use of groundwater for agricultural irrigation increases the rate of occurrence that can cause irreversible damage to human life and the environment (Shaban & Darwich 2011; Rahimi & Alexander 2013). Therefore, Karst formations are generally vulnerable to sinkhole occurrences and can be triggered by urbanization, climate change, and land-use and land cover regimes (Benhammadi & Chaffai 2015; Entezari *et al*., 2016).

Since the study area has great importance in terms of solar energy fields, agricultural activities, coal reserves, and planning to establish a thermal power plant after a few years, predicting and determining the sinkhole susceptibility areas become vital to ensure the economic income and prevent loss of investments. This high economic income also leads to the expansion of residential areas overlapped with limestone zones as existing in Karapınar city center is located on very limited and strong rock formations. In the literature, there are several studies focused on sinkhole occurrence prediction and generation of sinkhole susceptibility maps via Geographical Information Systems (GIS) (Özdemir 2015; Özdemir 2016; Orhan *et al*., 2020) Analytical Hierarchy Process (AHP) (Sarı 2017; Subedi *et al*., 2019), Multi-Criteria Decision Analysis Techniques (Sari *et al*., 2021) machine learning algorithms (Taheri *et al*., 2019) and frequency ratio (Elmahdy *et al*., 2020; Yong *et al*., 2020). These studies have focused on revealing the main reasons for sinkholes and determining the frequency of occurrence by considering several variables in topographic, geological and meteorological aspects. The MaxEnt method is used by Blazzard (2018) to examine climate relationships of Florida considering 9 variables which are related to climatic variables.

This study intends to move one step further to achieve more reliable and accurate predictions of sinkholes occurrence and susceptibility zones. The MaxEnt(Maximum Entrophy) model is applied to generate a sinkhole susceptibility map considering sinkhole occurrences are highly dependent on environmental, geological, topographic, meteorological, and anthropogenic factors as MaxEnt can reveal the spatial relationships among these factors. Besides assigning weights to variables, the MaxEnt model can determine the consistency of sample points in each variable and the intervals in which sinkholes usually occur. Thus, the weights and percent contributions are being determined by the MaxEnt model considering the sample distribution of points on variables. In this way, revealing and detecting the main reasons and mostly responsible variables for sinkhole occurrences may be specified without any user-defined weights or classifications and may be identified independently. In the study following criteria were selected; Mean annual temperature, isothermality, temperature seasonality, (Precipitation Seasonality), well density, wetness, precipitation, faults solar radiation, water vapor, geology, settlements, roads, elevation, land-use, and slope

2. Material Methods

Generating sinkhole susceptibility map starts with several processes to generate variable maps. MaxEnt method requires setting all variable maps in same resolution and geographic boundary. The flowchart of the study is given in Figure 1.

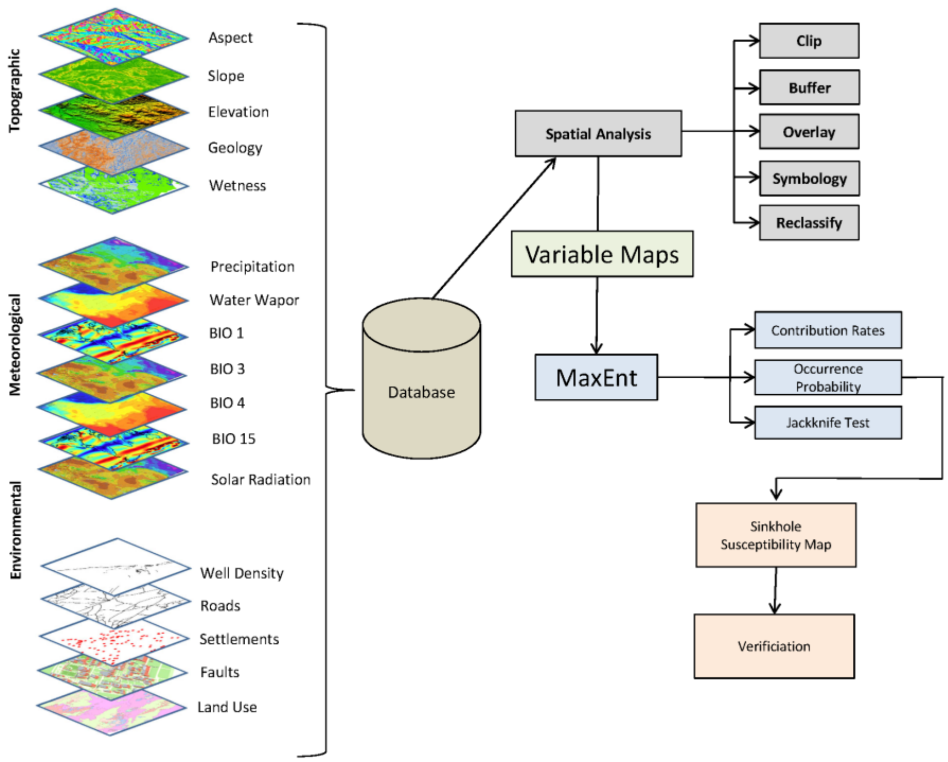

Fig. 1. Implementation model of the sinkhole susceptibility

2.1 Study area

The study area is located between 32°20’44.2’’ and 35°4’30.18’’ W longitude and 37°1’31.6’’ and 38°47’48.8’’ N latitude (in the WGS84 datum) with an area of 259.45 km^2, which refers to the named basin boundaries close to Konya. The study area boundaries are shown in Figure 2.

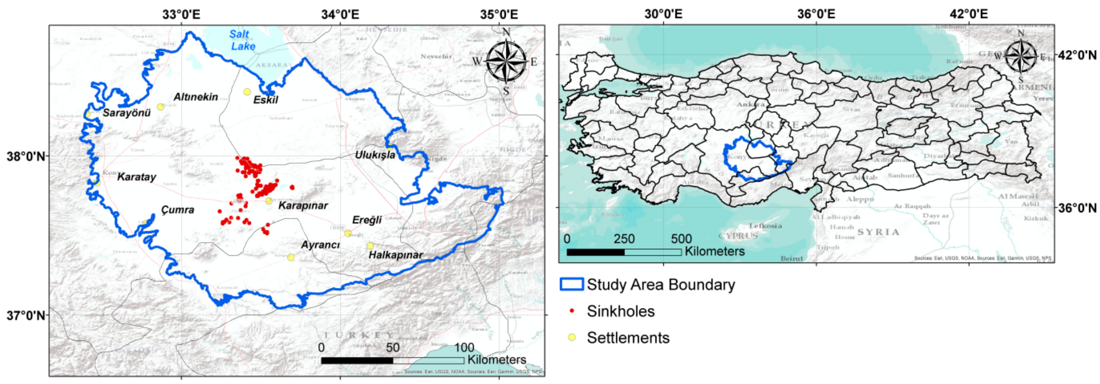

Fig. 2. The study area boundaries

The study area has very high temperatures in the summer season and a very cold climate in the winter season, with 24.3 °C and 2.1 °C on average. The study area has intensive agricultural activities with corn, sunflower, and sugar beet, as these crops require a high amount of water. Therefore, demand for water increases in the summer season, where groundwater is the primary source for irrigation. The sinkhole clusters are located on thick carbonate bedrocks as carbonate is highly susceptible to sinkholes. The geological map of the study area is shown in Figure 3.

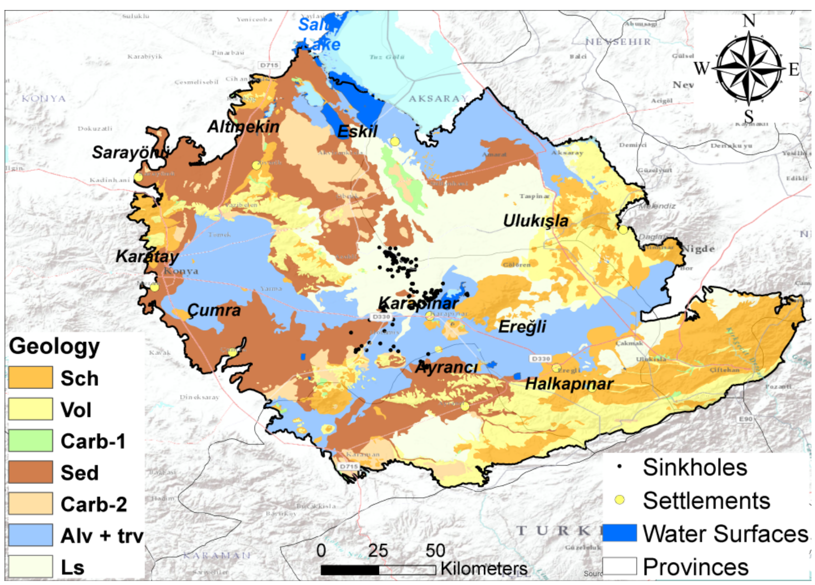

Fig.3. The geology map of the study area (Sch : Schist, Vol : Pyroclastic Rocks (Agg+tu+br), Carb-1 : Carbonate Rocks-1, Sed: Clastic Rocks (cong+ss+cs), Carb-2 : Carbonate Rocks-2, Alv+trv : Quaternary deposits, Ls : limestones). (Imperable-Semi Imperable Units: Sch, Pyroclastic Permeable Units: Others)

The sinkholes in the study area were defined as "cover-collapse" (Törk *et al*. 2013), and the ground collapse occurs when karstic limestone loses its strength due to several reasons as groundwater decreases, vibration, and decay. The main threat of this kind of sinkhole is the capability to occur abruptly, and usually, it is being difficult to predict and escape from it. When evaluating the locations of sinkholes, formation is a composition of marl-claystone intercalated with limestone. In the plateau area, where old sinkholes are intensely developed, alternating limestones and marls are generally observed. According to Ulu *et al*. (1994), the thickness of the formation is approximately 450 m (Ayday & Alan 2020).

2.2 Maximum Entropy (MaxEnt) Model

MaxEnt is an algorithm based on a machine learning system used to determine their spatial distribution by evaluating point positions and layers. MaxEnt uses occurrence data to estimate the probability distribution of varieties based on maximum entropy theory(Phillips *et al*., 2006; Elith *et al*., 2011). The MaxEnt model can estimate the spatial distribution probability of the samples by evaluating the variables by adjusting the probability distribution of the maximum entropy. These models are based on iterative comparison of predictive (independent) variable values in occurrence (entity) regions with a large subsample extracted from the study area and used as non-realization values (Phillips *et al*., 2006; Elith *et al*., 2011).

MaxEnt estimates the probability of an event's target distribution by determining the probability distribution of the maximum entropy. In detail, the model defines the most overlapping value of each observation point and independent variables to determine the spread of species in each variable (Phillips *et al*., 2006). Thus, the Maxent model requires presence data (existing sinkholes) and independent variables to determine the distribution. The sinkhole occurrence is considered to be species to predict its distribution and mostly occurring variables and intervals. MaxEnt software allows the user to generate probable distribution via several parameters for learning and graphical result outputs. MaxEnt generates verification and accurate outputs based on AUC (Area Under the Curve) measures and jack-knife method.

2.3 Data Specification

Several spatial datasets are used to generate sinkhole susceptibility that affects sinkhole occurrences. Bioclimatic variables are related to precipitation and evaporation of water resources and were retrieved from WordClim (URL 1) database at 30 seconds (1 km^2) resolution. Bioclimatic variables are also related to agricultural activities, and irrigation, as groundwater resources are mostly used for irrigation. Therefore, high temperatures and low precipitation rates increase the water demand. Land use map and Wetness criteria are retrieved from the CORINE project (URL 2) at 20 x 20 meters resolution. Considering the existing sinkhole locations, it has been observed that they mostly overlapped with agricultural lands and have a triggering effect on sinkholes due to intensive agricultural activities, movements, and vibrations of heavy agricultural vehicles. Digital Elevation Model (DEM) data is retrieved from the ASTER GDEM database at 30 x 30 meters resolution, where slope and aspect criteria are derived from DEM data at the same resolution. Faults and geology criteria are retrieved from the Turkish Directorate of Mineral Research and Exploration institute at 1/25.000 scale. As frequently mentioned in research and studies, geological formations and fault movements have a decisive role in the occurrence rate of sinkhole occurrence, and especially geological formations are the main factor in sinkhole occurrences. All the spatial variables and data resources are given in Table 1.

Table 1. Spatial data sources and units

Variables	Units	Data Source
BIO1 (Mean Annual Temperature)	C^O	WorldClim
BIO3 (Isothermality)	C^O	"
BIO4 (Temperature Seasonality)	C^O	"
BIO15 (Precipitation Seasonality)	C^O	"
Precipitation	mm/m^2	"
Solar Radiation	$(kJ\ m^{-2}\ day^{-1})$	"
Water Vapor	*kPa*	"
Geology	*Class*	1/25.000 Geology Map
Land-Use	*Class*	CORINE Project
Settlements	*Meter*	Derived from CORINE
Well Density	*%*	1/1000 Water Well Maps
Roads	*Meter*	OSM Database
Faults	*Meter*	1/25.000 Faults Map
Elevation	*Meter*	ASTER GDEM
Aspect	*Class*	Derived from ASTER GDEM
Slope	*%*	Derived from ASTER GDEM
Wetness	*Class*	Copernicus Web Site

3. Generating Sinkhole Occurrence Probability

To determine the sinkhole occurrence probability map via the MaxEnt model, all the variables given in Table 1 were uploaded to MaxEnt software. Current geographical distributions of sinkholes in Karapınar region were examined. In total, 145 existing sinkholes were considered where %70 of them as sample data and %30 of them as test data to verify the model. Sample and test point distributions are shown in Figure 4.

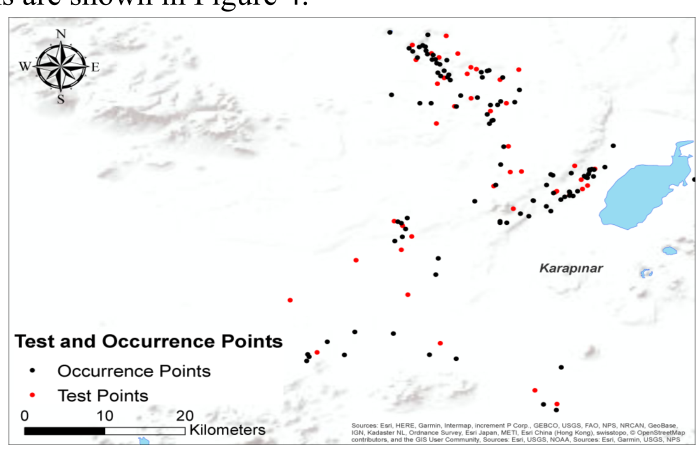

Fig. 4. Distribution of defined 100 sample and 45 test sinkhole points

The verification of the model can be done by using the AUC values of both sample and test data. The AUC values were obtained for the training data with 0.978 and for the test data with 0.963, where both values are quite similar and consistent. The AUC values also revealed that generated sinkhole susceptibility map is reliable and accurate. The AUC values and graphics are given in Figure 5.

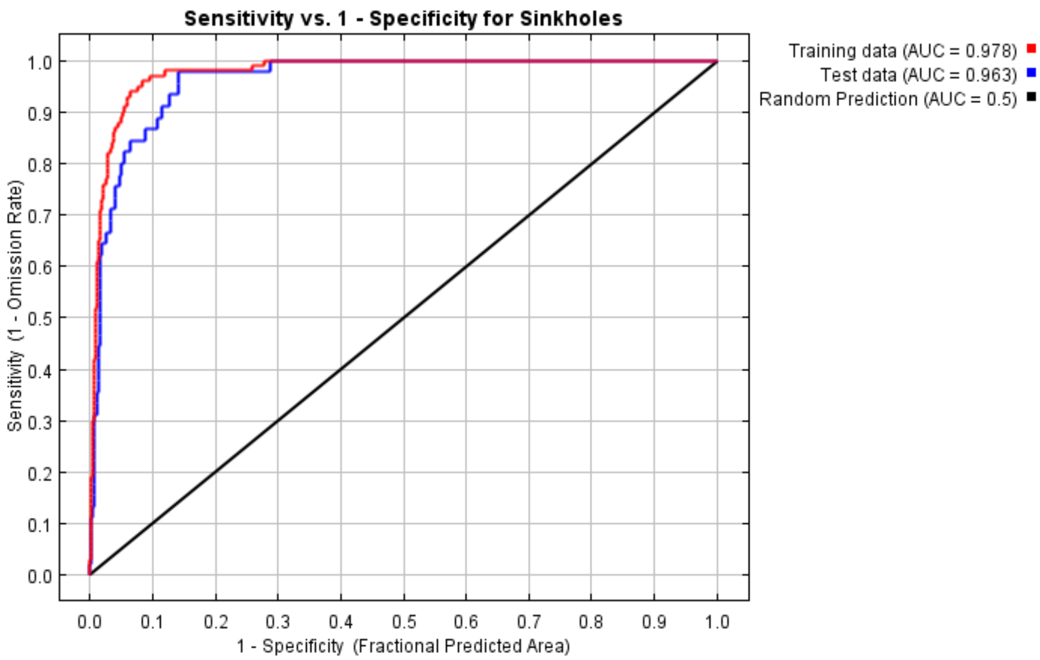

Fig. 5. AUC values for training and test dataTo determine the relativity of variables in terms of sinkhole occurrences, Jackknife test option in MaxEnt modeling software was used. As can be seen in Figure 5, mean annual temperature, precipitation seasonally, Geology and Precipitation variables were determined as highly responsible for sinkhole occurrence when examining randomly selected 100 existing sinkholes. While geological formations are the main decisive factors of sinkhole occurrences, precipitation and temperature are related to groundwater level decreasing which has a triggering effect on sinkholes. When used for insulation, the variables with the highest value are the annual average temperature, which alone seems to have the most useful information. The environmental variable that reduces the value the most when omitted is Geology, so it seems to have the most information not found in the other variables. Aspect, slope, faults, and wetness were determined as non-related to sinkhole occurrences, and as a result, 100 sinkhole locations were intersected with these variables without consistency. Besides this, elevation and isothermality can be accepted as highly related to sinkholes occurrences and should be considered. To determine the similarity and reliability of the MaxEnt sinkhole occurrence, a jackknife graphic was generated for only 45 test sinkhole locations (Figure 6). When jackknife graphics of both sample and test data were compared, it was found that the similarity results and the responsible variables were very similar to each other. This similarity can be accepted as one of the most effective ways to verify the MaxEnt sinkhole occurrence probabilities.

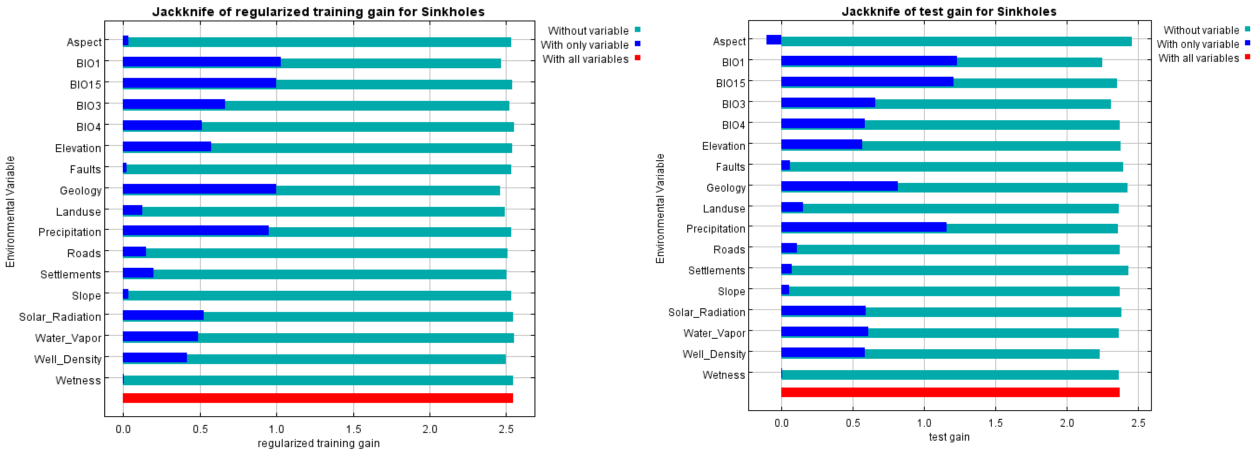

Fig. 6. Jackknife test results of training data and variables

At each iteration of the training algorithm, the increase in regular gain is added to the corresponding value in the initial guess. The values of the relevant variable on the training entity and background data are then randomly allowed as a second guess for each variable in turn. The model is standardized to the resulting decline in training AUC as a percentage and reassessed on allowable data. Estimates of the weights of the variables are given in Table 2.

Table.2. Spatial datasets, units and retrieved data sources

Variable	Percent Contribution	Variable	Percent Contribution
Geology	**34.9**	BIO3	**1.6**
BIO15	**18.8**	Faults	**1.3**
BIO1	**14**	Aspect	**0.7**
Land-Use	**6.9**	Water Vapor	**0.6**
Well Density	**6.7**	Elevation	**0.4**
BIO4	**5.8**	Precipitation	**0.4**
Solar Radiation	**3.2**	Wetness	**0.2**
Settlements	**2.7**	Slope	**0.0**
Roads	**1.7**		

To evaluate each variable and determine how each variable affects the MaxEnt prediction, response curves were generated. The curves show the marginal effect of changing precisely one variable, whereas the model may also take advantage of sets of variables changing together. In other words, response curves are helpful to detect the intervals of maximum effect of each variable to the prediction. The response curves also reveal the consistency of the variables considering all the sample data and their distribution within a variable. All the response curves are shown in Figure 7.

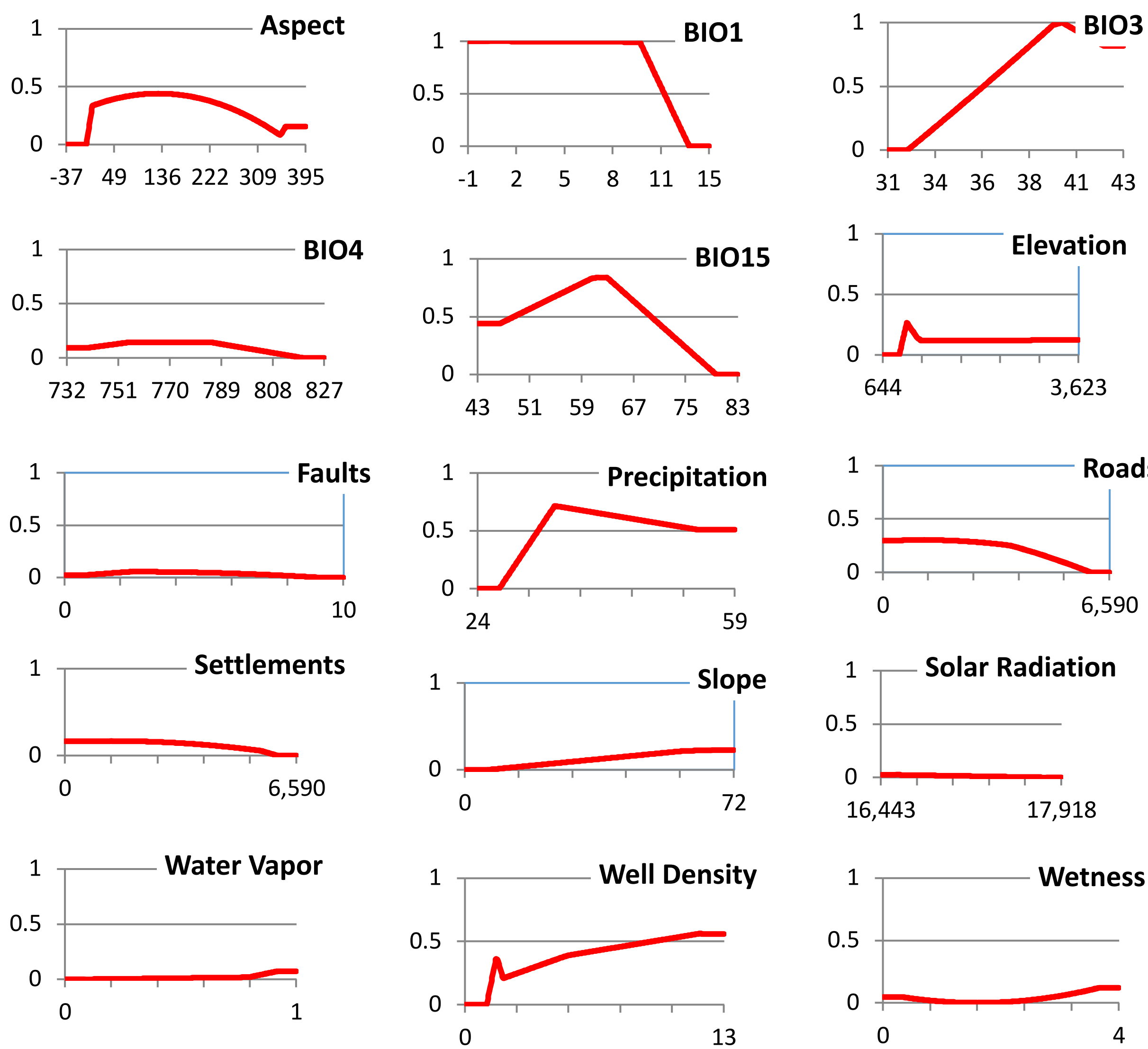

Fig.7. Response curves of each variable (1 = has highest relationship, 0= has no relationship)

All response curves of the variables have the same scale on the vertical axis; 1 denotes the highest correlation with sinkhole formation, 0 denotes relatedness with sinkhole formation. The horizontal axis of the graphs shows the minimum and maximum value of each variable in different units. Response curves are also useful for detecting specific ranges or values with the highest correlation of a variable through chart selections. For example, the variable BIO1 has a very high correlation with sinkhole formation, up to a value of 10, and becomes 0 when BIO1 reaches 13.5.

Geology and land-use response curves within categorical variables are shown in Figures 8 and 9. Sinkholes were mostly overlapped with Grasslands, Semi-Agricultural Lands, Pastures, and Sclerophyll land-use classes, where generally agricultural lands are accepted as highly susceptible to sinkholes (Figure 8). When considering the geological formations response curves, sinkholes were mostly overlapped with limestone karstic formations as they are the most prone to sinkholes (Figure 9).

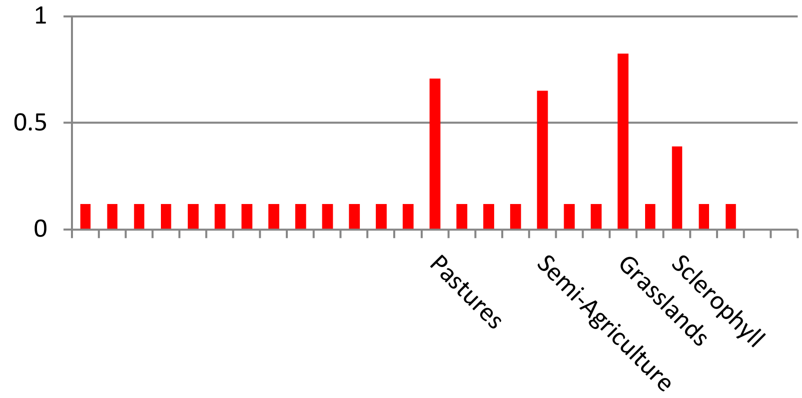

Fig. 8. Response curves of land-use variable (1-11 Urban areas, 12-22 Agricultural lands, 23-25 Forests, 26-31 Semi-natural areas)

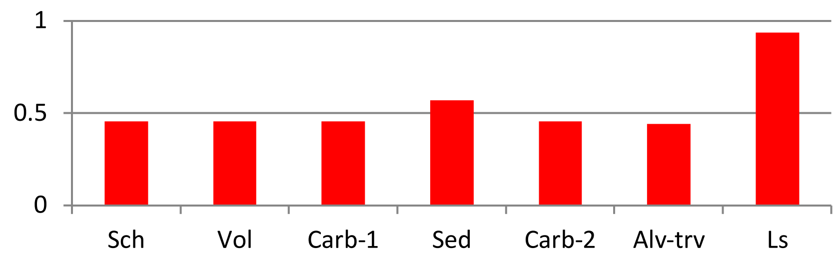

Fig. 9. Response curve of geology variable (The geological formations of the study area (Sch, schist; Vol, pyroclastic rocks (Agg+tu+br); Carb-1, carbonate rocks-1; Sed, clastic rocks (cong+ss+cs); Carb-2, carbonate rocks-2; Alv+trv, quaternary deposits; Ls, limestones) (imperable-semi imperable units, Sch; pyroclastic permeable units, others)

4. Discussion

Finally, a map of the regions susceptible to a possible sinkhole formation was created with the MaxEnt software (Figure 10). Accordingly, it has been determined that 458.52 km^2 of the study area is very vulnerable to sinkhole formation. Considering the existing and possible sinkholes, they are located close to the center of Karapınar and are very clearly clustered. The Natural Breaks Jenks Method was used to classify the areas susceptible to sinkhole formation. Most of the sinkholes outside the center of Karapınar are expected to occur on the Çumra region in a short time, following the limestone formations and intensive agricultural lands.

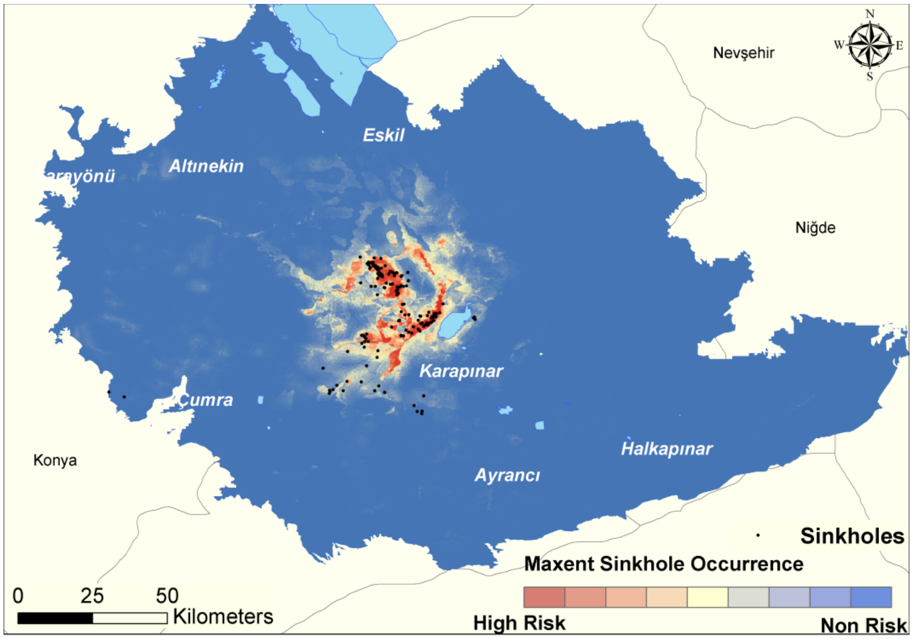

Fig. 10. MaxEnt possible sinkhole occurrence distribution map and risk zones

Another verification was performed to evaluate the overlap of 45 test sinkholes with a generated possible sinkhole distribution map. 27 of them (over 0.80) overlapped with highly susceptible areas and 11 (0.60-0.80) overlapped risk areas moderately. Only 8 of 45 test sinkholes were overlapped with non-risk zones, which are quite small compared to others (1-3 meter radius), and distributions were given in Figure 11.

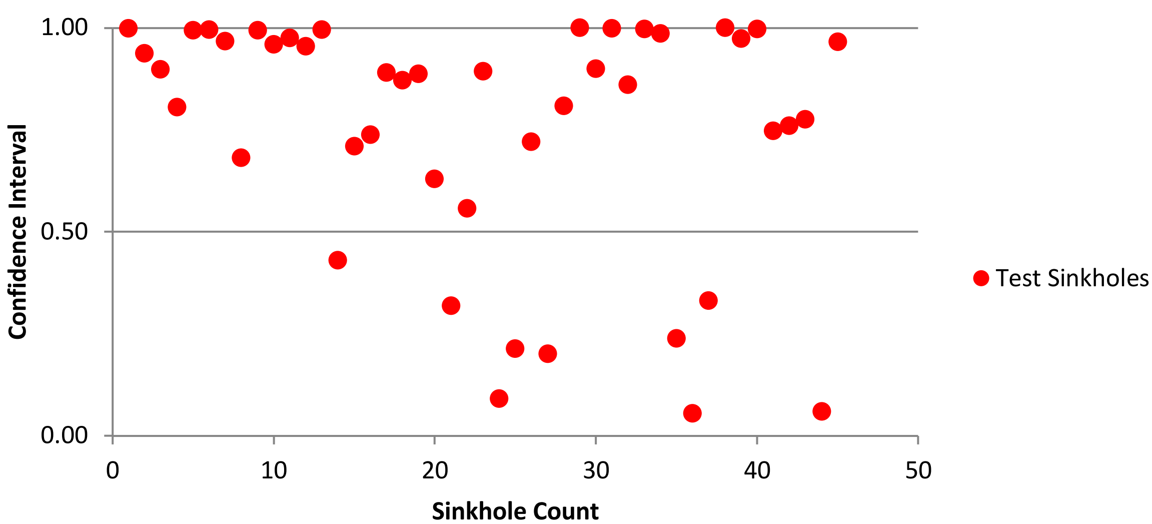

Fig. 11. Overlap of 45 test sinkholes points and MaxEnt risk values

The overlap of the test sinkholes and generated possible sinkhole distribution map are shown in Figure 12. Considering both high and moderate risk zone classes, 84.4 % of the test points overlapped with risk zones that can be accepted as reliable and accurate.

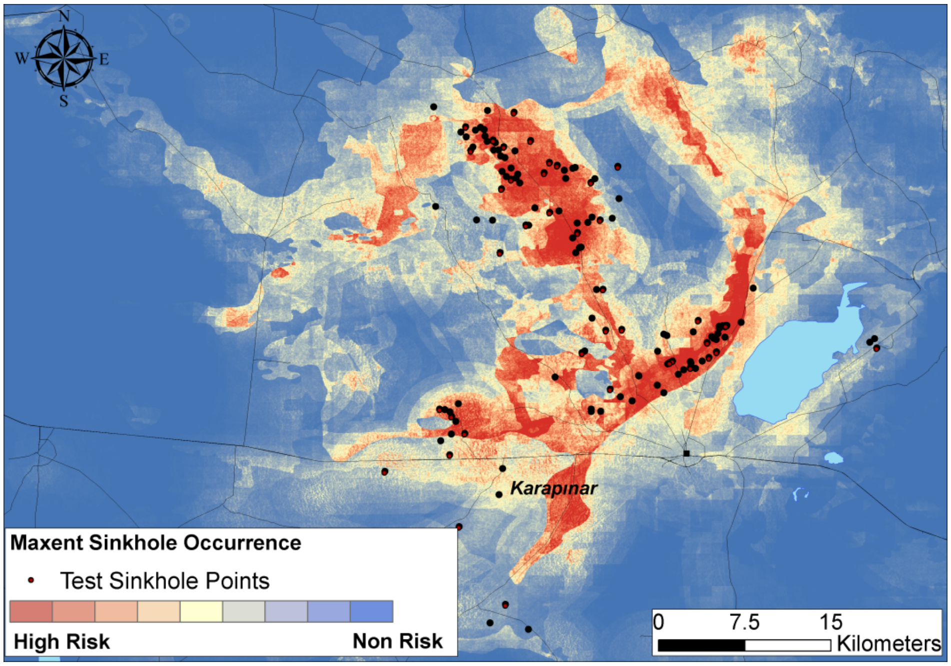

Fig. 12. Overlap of 45 test sinkholes points and MaxEnt possible sinkhole occurrence map

This study represents the relationship between variables and sinkhole occurrence probability by evaluating the spatial interaction of sinkholes without any user-defined parameter or weight. MaxEnt method determines this spatial relationship like Multivariate Statistical Analysis (D'Angella *et al*., 2015) and Frequency Ratio (Yılmaz 2007; Ozdemir 2015). On the other hand, most of the studies used techniques that require user-defined parameters based on Weighted Overlay and Multi-Criteria Decision Analysis methods (Oh & Lee 2010; Nachbaur & Rohmer, 2011; Al-Kouri *et al*., 2013; Perrin *et al*., 2015; Subedi *et al*., 2019; Orhan *et al*., 2020; Sarı *et al*., 2021). These techniques require user-defined weights and the weights are generally flexible due to the included variable counts and sinkhole distributions. When evaluating the weights, geology criteria were chosen as highest weight (Taheri et al., 2019; Subedi et al., 2019; Orhan et al., 2020; Sarı et al., 2021) other criteria weights have been specified differently than each other. Therefore, sinkhole occurrence probabilities were determined more realistic in MaxEnt method due to the excluded human-defined parameters.

5. Conclusion

This study presents the sinkhole occurrence predictions via the MaxEnt model by evaluating the sinkholes' similarity and reveals valuable information about factors that trigger sinkholes. Although this study aims to generate a susceptibility map for sinkholes, considering the economic value of the study area, risk zones were generated to guide investments and projects such as solar energy field location determination, agricultural crop management, environmental planning, suitable site selection for urban settlement areas, irrigation and highway planning projects. Solar energy panels, cultural heritage, agricultural productivity, petroleum research investments, and coal reserve research structures are being threatened by sinkholes occurrence probability.

The growing rate of this natural disaster reveals stress on organizations and institutes to specify the prediction of sinkhole occurrences and prevention procedures urgently. The recent research generated sinkhole susceptibility maps via user-defined weights, intervals, and coefficients by using several methods. However, the sinkhole occurrences should be evaluated within its nature by only specifying the effects (variables) that trigger sinkhole formations. Thus, the MaxEnt method allows researchers to generate sinkhole locations that will probably occur by evaluating recent sinkhole locations and their similarity, intersection, and dependencies to variables regardless of user-defined specifications. Therefore, the most reliable and accurate susceptibility maps can be determined via the MaxEnt method. Additional criteria such as geodetic deformation measurements with GPS systems, groundwater level decreasing, and groundwater observations (level, chemical, and physical analysis) should be included to characterize the area more precisely and to take efficient and necessary precautions as soon as possible

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