RESEARCH PAPER

FLOOD SUSCEPTIBILITY MAPPING USING LOGISTIC REGRESSION ANALYSIS IN LAM KHAN CHU WATERSHED, CHAIYAPHUM PROVINCE, THAILAND

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ABSTRACT. Due to Tropical Storm Dianmu's influence in the Lam Khan Chu watershed (LKCW) area, central Thailand saw its worst flood in 50 years from September 23 to September 28, 2021. The flooding lasted for 1-2 months. The objective of this research is to study flood susceptibility using logistic regression analysis in LCKW area. According to the study 11 floods occurred repeatedly between 2005 and 2021, in the southern of Bamnetnarong district and continued northeast to Chaturat district and Bueng Lahan swamp. These areas are the main waterways of the LKCW area, the Lam Khan Chu stream and the Huai Khlong Phai Ngam, for which the dominant flow patterns are braided streams. The main factors influencing flooding are geology, stream frequency, topographic wetness index, drainage density, soil, stream power index, land-use, elevation, mean annual precipitation, aspect, distance to road, distance to village, and distance to stream. The results of the logistic regression analysis shed light on these factors. All such variables were demonstrated by the β value coefficient. The area's susceptibility to flooding was projected on a map, and it was discovered to have extremely high and high levels of susceptibility, encompassing regions up to 148.308 km^2 (8.566%) and 247.421 km^2 (14.291%), respectively, in the vicinity of the two main river sides of the watershed. As a result of this research the flood susceptibility map will be used as a guideline for future flood planning and monitoring.

KEYWORDS: flood susceptibility, logistic regression analysis, Lam Khan Chu watershed, Chaiyaphum, Thailand

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INTRODUCTION

Floods are major natural disasters on a global scale that can cause significant damage to life and property (Faiz et al. 2018; Maleki et al. 2020; Leal et al. 2021). It can be seen from the statistics of The Emergency Event Database (EM-DAT), which has recorded flood events all over the world, found that in 2021 there were 223 flooding events (CRED 2022). There are many factors affecting the occurrence of floods, including the occurrence of thunderstorms caused by low-pressure patches over the terrain, the Intertropical Convergence Zone across the low-latitude tropical region, and low-latitude tropical cyclone formation from turbulence, inevitably causes rain to soak for a long time (Sarjito et al. 2022; Purwanto et al. 2021). There are also additional factors that make territory more vulnerable to flooding, which are all caused by human activities such as building water barriers, urbanization, agricultural expansion, land-use change, including deforestation (Camara et al. 2020; Coetzee 2022; Waiyasusri and Chotpantarat 2022) catalysts the severity of floods and increases the frequency of flooding.

The floods in Thailand occur every year, especially during the monsoon season in May-October of each year (Tomkrtoke and Sirisup 2022; Rojpratak and Supharatid 2022). Tropical Storm Dianmu, which developed in the South China Sea and travelled west towards Vietnam, Laos, and Thailand between September 23 and September 28, 2021, had a significant impact on a catastrophic flood that occurred in central Thailand during that time (Thodsan et al. 2022). Tropical Storm Dianmu has created a massive rainstorm that lasted six days, causing flooding in 30 provinces in Thailand, leaving 6 dead and 2 missing (AHA centre 2021). It makes Lam Khan Chu Watershed (LKCW), which is an upstream area of Chi watershed in Chaiyaphum Province, in the north-eastern region of Thailand, with an area of 1731.289 km^2, prone to frequent flooding during the monsoon season (July-October of every year). This has caused considerable damage to communal and agricultural areas. Tropical Storm Dianmu had an impact on LKCW between September 23 and September 28 of 2021, causing the worst flooding in 50 years. The incident caused damage in the along the Huai Lam Khan Chu stream, affecting riverbank overflows and flooding up to 3-4 meters, affecting communities, agricultural areas, and transport routes in the Bamnetnarong district, Chaturat district, and Chaiyaphum Province, flooded lasting 1-2 months. Another reason for the great flooding is that the topography of LKCW is an upstream area with relatively low slopes and wide plains, coupled with land-use dominated by agriculture. And there is very little forest area upstream, which prevents rainfall from being retained in upstream forests and causes it to quickly become surface runoff into the downstream area.

Application of geo-informatics technology plays an important role in the analysis of current disaster management, especially in flooding. This is because it is a technology that can display spatial data and determine the coordinates and relationships of various variables that affect floods. For this reason, flood susceptibility mapping needs to be designed from a common database of hydrological, meteorological, geological and anthropogenic factors (Khosravi et al. 2016; Waiyasusri et a. 2021; Ghasemlounia and Utlu 2021). Typically, flood susceptible areas are analysed using hydrologic and hydraulic modelling approaches with field-based measurements or remote sensing data is used to feed the database into the analysis model (Maan et al. 2020; Bharath et al. 2021; Chauhan et al. 2022). However, statistical analysis principles were developed based on spatial models to conduct flood susceptibility studies to determine its behaviour (Nguyen et al. 2020; Suharyanto 2021; Khiavi et al. 2022). In terms of statistical principles for finding flood-risk areas, it is important to be able to analyse many variables and to analyse a wide area to see the distribution of flood-risk areas (El-Fakharany et al. 2021). In addition, the progress of geo-informatics technology can analyse and process various database sets compiled from past to present. The technology can effectively assess flood-susceptible areas and show good effectiveness.

The most popular educational approaches for flood susceptibility mapping are univariate models (Zhang et al. 2018; Li et al. 2018), multivariate models (Tosunoglu et al. 2020; Jane et al. 2020), and artificial neural network (ANN) models (Elsafi 2014; Dahri et al. 2022). Still, the technique has limitations on the complexity of database manipulation and processing that requires high levels of computer memory hardware and long analytics when using a large number of variables. Other models such as the Frequency Ratio (Ramesh and Iqbal 2022; Jaiswal et al. 2022), Analytic hierarchy process (Mitra et al. 2022; Ekmekcioğlu et al. 2021), and Logistic Regression (Al-Juaidi et al. 2018; Chowdhuri et al. 2020; Kim et al. 2020) also received attention, but not as much as the ANN model. For this reason, logistic regression analysis (LR) may be a better alternative statistical analysis procedure in flood susceptibility studies. Because it can analyse multiple geographic database sets, and databases that are continuous and categorical data. This can be seen from research that studies flood susceptibility in different regions of the world, such as the assessment of flooded areas in Jamaica that has applied LR. Importantly, the relevant variables are local geology, geomorphology, hydrology and land-use (Nandi et al. 2016). In Fujian Province, China, techniques of geodetector, certainty factor, and logistic regression were applied to establish a frame for the flash flood susceptibility assessment. According to empirical results the model achieves the highest degree of accuracy in terms of the success rates (Cao et al. 2020). Although Iran is an arid region, it experiences flash floods in the Haraz watershed in Mazandaran Province. The research introduced key parameters for assessing flood-sensitive areas: altitude, slope angle, plan curvature, Topographic Wetness Index (TWI), Stream Power Index (SPI), distance from river, rainfall, geology, land-use, and Normalized Difference Vegetation Index (NDVI) are all important variables (Bui et al. 2019). Even in the southern Gaza Strip areas, LR was applied to assess flood susceptible areas until the proposed model is robust with very reasonable accuracy (Al-Juaidi et al. 2018). However, it is crucial that the variables that are being added to the model be moderated before they are used in the study. As a study by (Tehrny et al. 2017), 15 flood conditioning factors were compiled and included geo-databases: altitude, slope, aspect, geology, distance from river, distance from road, distance from fault, soil type, land-use, rainfall, Normalized Difference Vegetation Index, SPI, TWI, STI, and curvature were analysed for LR and the results showed the highest prediction rate of 90.36%. (Hamid et al. 2020) studied the sensitivity of flash flood hazard using geospatial techniques, and analysed key variables such as elevation, slope, distance from the network, land-use, density of the drainage, flow accumulation, surface roughness, SPI, TWI, and curvature were analysed in Khartoum area, Sudan. When considering the variables, geography variables are considered first in the study process in which the data is generated from a digital elevation model (DEM). (Lim and Li 2018) in a study of flood mapping using multi-source remotely sensed data and LR in the heterogeneous mountainous regions in North Korea, found that DEM data that can be analysed for terrain should be of high resolution between 1-30 meters to be able to analyse terrain analysis as well. (Chen et al. 2020) using a machine learning technique for flood mapping in the Yangtze River Delta, China identified rainfall variables that are important for model analysis and can also be a catalyst for flooding. For this reason, LR was applied in this research to find flood susceptibility and mapping for floods in the future, specifically in accordance with the principles of the United Nations Sustainable Development Goals (SDGs), Goal 13 addresses: Take urgent action to combat climate change and its impacts (Department of Economic and Social Affairs 2022). It defined climate change as one of the main causes of natural disasters that are more frequent and likely to intensify, causing enormous losses to people's lives and property, as well as having broad economic and social impacts, especially at the community and local level with limited disaster response capacity.

The objective of this research was to study flood susceptibility using logistic regression analysis in Lam Khan Chu Watershed, Chaiyaphum Province, Thailand, by using spatial database that affects flooding in preparing a flood susceptibility map in LKCW. The study guideline has compiled variables that affect the occurrence of floods, as physical factors such as elevation, slope, aspect, stream power index (SPI), sediment transport index (STI), topographic ruggedness index (TRI), topographic wetness index (TWI), stream frequency (SF), drainage density (DD), infiltration number (IN), mean annual precipitation, geology, soil, and distance to stream; and the socio-economic factor involved and provide flood, and are important variables that used in flood applications including land-use, distance to village, and distance to road. This study is able to predict the factors of influential flood causing variables on flood occurrence. By developing a geographical database for simple management of flood risk regions for sustainable solutions to probable future flooding, the research results will be applied as a guideline for planning and monitoring in the event of future floods.

MATERIALS AND METHODS

Study area

Lam Khan Chu Watershed is a sub-watershed of the Chi watershed. The study area is located between latitudes 15°15′ N to 15°40′ N and longitude 101°20′ E to 102°E. The total study area is approximately 1731.289 km^2. LKCW area covers Thep Sathit, Bamnetnrong, Chaturat, and Sap Yai districts in Chaiyaphum Province, and covers part of Theparak district, Nakhon Ratchasima province (Fig. 1). The topography in the study area has an altitude of between 186-819 meters above mean sea level. The western part is a high mountain range, with the highest point of the LKCW area in the northwest of the study area. Elevation of 819 meters, located in Pa Hin Ngam National Park, is an important watershed forest area in the study area. An undulating plain with a small slope that slopes of the research area makes up the majority of the study area. It appears that the lowest point of the study area is Bueng Lahan, which is an important wetland in this region. The elevation of the terrain is 186 meters. The drainage pattern of the LKCW is a parallel drainage pattern, i.e., there are tributaries flowing dendritic-parallel to the main waterway. There is a direction of flow from west to east. The geological features in the study area are homogeneous, consisting of sedimentary rock covering the entire study area. The Korat group is a group of rocks that belong to the Jurassic–Cretaceous (210-66.4 million year) period, namely the Phu Kradueng formation, Phra Wihan formation, Sao Khua formation, Phu Phan formation, Khok Kruat formation, and Maha Sarakham formation, respectively, and Alluvial deposits in Quaternary (1.6-0.01 million year) covered the downstream area of LKCW around Bueng Lahan swamp.

The sedimentary rocks are described below: Quaternary deposits (Qa) consists of fluvial deposits, Maha Sarakham formation (KTms) consists of sandstone and rock salt, Khok Kruat formation (Kkk) consists of siltstone and sandstone, Phu Phan formation (Kpp) consists of siltstone and conglomerate, Sao Khua formation (Ksk) consists of siltstone and sandstone, Phra Wihan formation (JKpw) consists of quarzitic sandstone and conglomerate, and Phu Kradueng formation (Jpk) consists of siltstone and claystone.

Data

For the preparation of data in this research, Secondary data from various sources were collected for the analysis of flood recurrence areas in the LCKW, in particular the Actual flood area data for 2005-2021 and spatial data for the analysis of factors contributing to flooding, collecting data as follows: physical factors such as elevation, slope, aspect, SPI, STI, TRI, TWI, SF, DD, IN, mean annual precipitation, geology, soil, and distance to stream. Socio-economic factors that are relevant and provide for flooding, and are considered the most important variables used in flood work are land-use, distance to village, and distance to road (Table 1). All data are generated in raster database format, grid cell size 30x30 m.

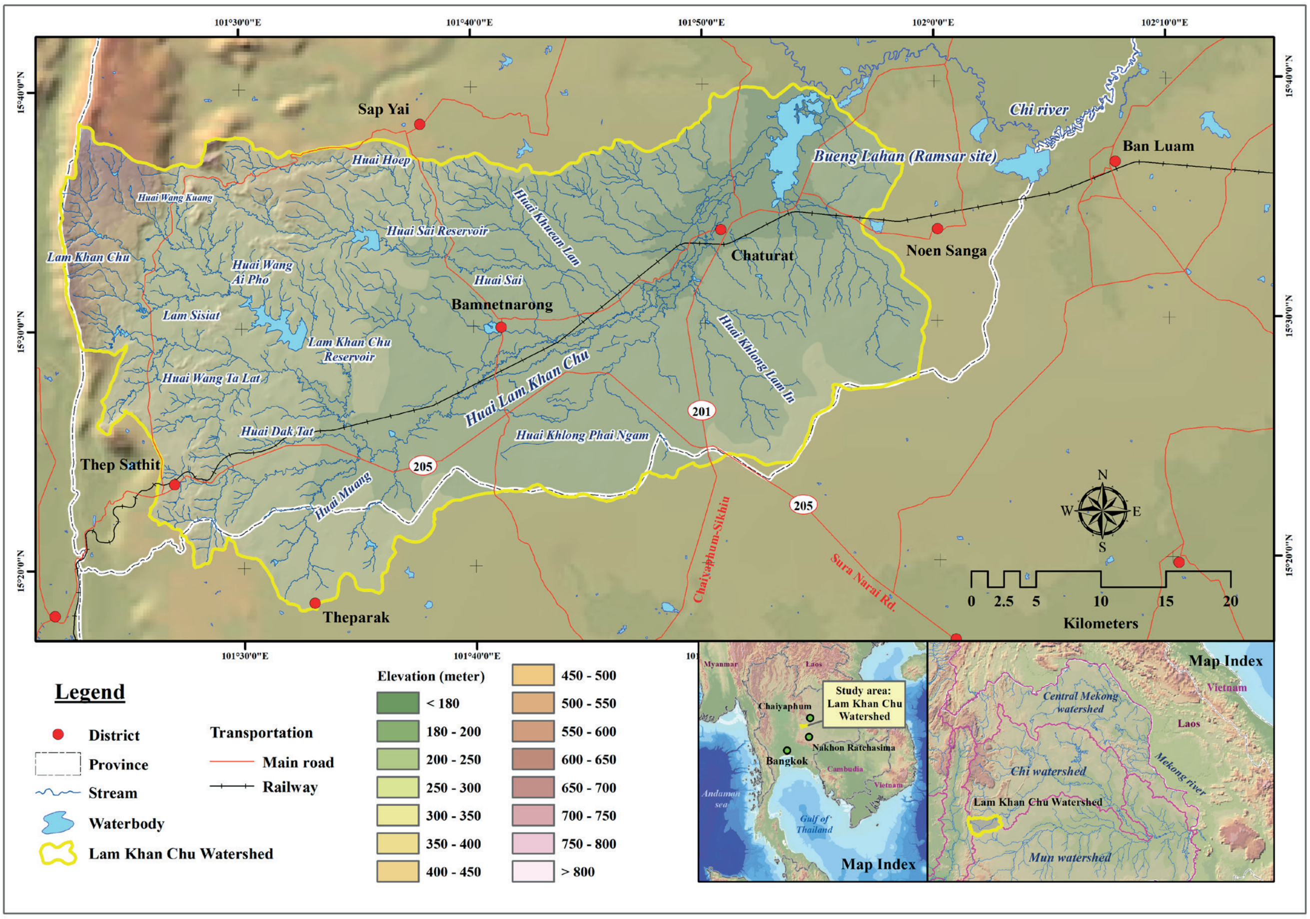

Fig. 1. Geographic map of the Lam Khan Chu Watershed area, Chaiyaphum Province

Table 1. Spatial data layers used in this research

Driving Factor	Variable (Theme)	Year	Source
	Actual flooding area	2005-2021	Derived from Geo-Informatics and Space Technology Development Agency (public organization) (GISTDA)
Physical factor	Elevation (Digital Elevation Model-DEM)	2020	Derived from Royal Thai Survey Department (RTSD)
	Slope	2020	Derived from the DEM
	Aspect	2020	Derived from the DEM
	Stream Power Index (SPI)	2021	Derived from the DEM
	Sediment Transport Index (STI)	2021	Derived from the DEM
	Topographic Ruggedness Index (TRI)	2021	Derived from the DEM
	Topographic Wetness Index (TWI)	2021	Derived from the DEM
	Stream Frequency (SF)	2021	Derived from the DEM
	Drainage Density (DD)	2021	Derived from the DEM
	Infiltration Number (IN)	2021	Derived from the DEM
	Mean annual precipitation	2005-2020	Derived from Thai Meteorological Department (TMD)
	Geology	2017	Derived from Department of Mineral Resources
	Soil	2017	Derived from Land Development Department (LDD)
	Distance to stream	2021	Derived from Department of Water Resource, Thailand
Socio-economic factor	Land-use	2020	Derived from Land Development Department (LDD)
	Distance to village	2021	Derived from Royal Thai Survey Department (RTSD)
	Distance to road	2021	Derived from Department of Public Works and Town &Country Planning.

Method

The research process consists of the following steps, as shown in Fig. 3 (1): flood prone area analysis, (2) spatial database analysis of driving factors, and (3) statistical approach. The details of each step are briefly explained below (Fig. 2).

Flood prone area analysis

The past occurrences records analysis may estimate future flood hazard events (Degiorgis et al. 2012; Tehrany and Kumar 2018). The first step for the analysis of flood susceptible areas is to analyze past events that tend to occur in the same area and the environmental variables that affect the flooding there. The Geo-Informatics and Space Technology Development Agency (public organization) (GISTDA) has analyzed and synthesized flood data from satellite imagery from various sources and compiled into a database system that can be used from the source https://flood.gistda.or.th/. Next, the flood prone area was generated from actual flood area during 2005 to 2019 using overlay analysis tools in GIS, obtained repeated flooding data over the past 16 years and then analyzed to determine the proportion of flooded area in the LKCW area, and those flood prone area data were analyzed for logistic regression in the next step.

Spatial database analysis of driving factors

The selection of factors affecting flooding is important for the flood susceptibility analysis to obtain accurate spatial results. In this study, the most related and repeated flood conditioning factors selection is crucial (Tehrany et al. 2015; Rahmati et al. 2019).

The first important data for this research study is Elevation (DEM) data obtained from the Royal Thai Survey Department (RTSD) in shapefile format, namely elevation point data, contour line data, stream line data, water bodies and watershed boundary. Most of the initial source data from the Royal Thai Survey Department (RTSD) are vector data, and thus are difficult to statistically analyze in research. Therefore, such vector data must be converted into a raster showing the statistical grid, especially digital elevation. The data was analyzed by spatial analysis by Topo to Raster technique in ArcGIS 10.2 software. The result was DEM data of 30x30 m grid cell size (Fig. 3a) for subsequent analysis of other variables. The local topographic slope (Fig. 3b), aspect (Fig. 3c), SPI (Fig. 3d), STI (Fig. 3e), TWI (Fig. 3f), TRI (Fig. 3g), SF (Fig. 3h), DD (Fig. 3i), and IN (Fig. 3j), were then calculated from the DEM. Flood prone areas are generally at low elevation and with a low degree of topographic slope (Kia et al. 2012). Aspect data, spatial data showing the direction of the slope, is an important component in determining the direction of water flow in high-slope terrain (Mojaddadi et al. 2017). The hydrological factors such as SPI, STI, TRI, and TWI also have considerable impacts on flood creation (Tehrany et al. 2017).

Stream power index (SPI) is the most widely used variable in flood susceptibility research. This is because it is a variable that indicates the potential for river currents to cause erosion. For this reason, such variables play a role in altering the surface condition of the terrain. The results show negative values for areas with topographic potential deposition and positive values for potential erosive areas. The SPI analysis can be calculated from Equation 1 (Moore et al. 1991; Tehrany et al. 2017):

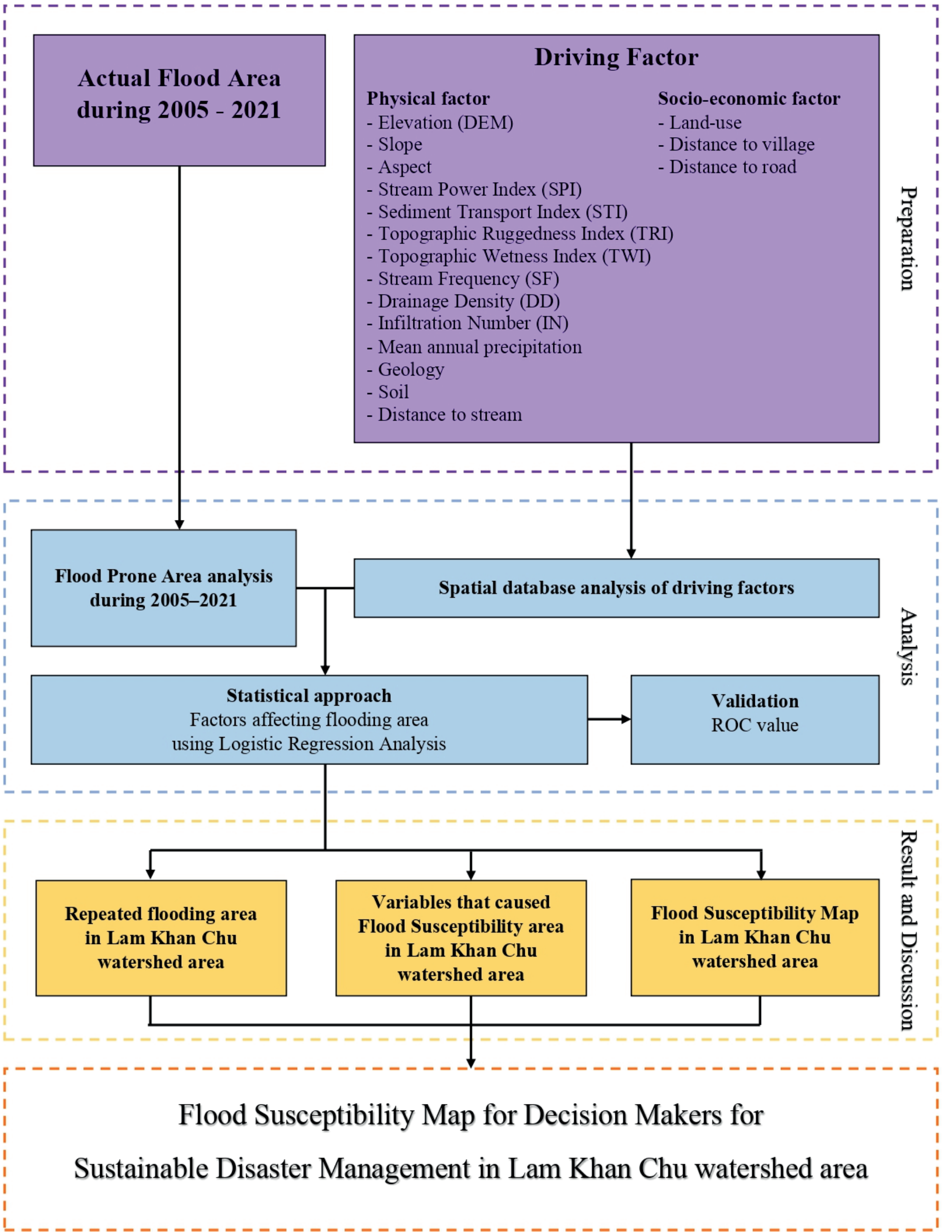

Fig. 2. Flowchart of methodology

$$SPI = A_S \tan\beta \qquad (1)$$

Where, A_s indicates the definite catchment area, and β denotes the slope gradient.

Sediment transport index (STI) is another variable that defines the movements of the sediments due to the water movement. The erosion and deposition processes are characterized using STI (Mojaddadi et al. 2017). The results obtained with a high level of STI indicate an area of high sedimentation. Conversely, a low level of STI indicates an area of low sedimentation. STI analysis can be calculated from Equation 2:

$$STI = \left(\frac{A_s}{22.13}\right)^{0.6}\left(\frac{\sin\beta}{0.0896}\right)^{1.3} \qquad (2)$$

Where, A_s indicates the definite catchment area, and β denotes the slope gradient.

Topographic wetness index (TWI) is a watershed-forecasting index and an indicator of the tendency for water to flow to a basin based on gravity (Chen and Yu 2011). High TWI values indicate areas prone to water accumulation in the basin, which may occur in lowland, low slope or basin areas. The TWI analysis can be calculated from Equation 3 (Hamid et al. 2020):

$$TWI = \ln\left(\frac{A_S}{\tan\beta}\right) \qquad (3)$$

Where, A_s indicates the definite catchment area, and β denotes the slope gradient.

Topographic ruggedness index (TRI) provides a quantitative measure of terrain heterogeneity. TRI is a geomorphological variable that is related between the elevation of the terrain and the flood area (Werner et al. 2005). The results obtained with high levels of TRI indicate areas of high roughness appearing on the terrain, while low levels of TRI indicate relatively flat terrain. The TRI analysis can be calculated from Equation 4 (Tehrany et al. 2017):

$$TRI = Y\left[\sum \left(x_{ij} - x_{00}\right)^2\right]^{1/2} \qquad (4)$$

Where, x_{ij} is elevation of each neighbor cell to cell (0,0).

Stream frequency (SF) is the ratio between the numbers of first-order streams to the watershed area. As a result, a high SF indicates an area with a low runoff, refers to the flow of water in a stream from upstream to downstream slowly and takes a long time. A low SF value indicates that the water flow in the stream flows quickly. The SF analysis can be calculated from Equation 5 (Horton 1932):

$$SF = \frac{\sum Ns}{A} \quad (5)$$

Where, N_s is the total number of first order streams and A is the total watershed area (km^2).

Drainage density (DD) is the ratio of the total stream length per watershed area. The result of the DD value, if the DD value is greater than 3, the watershed area has a drainage at the level of well drainage, if the value is between 1 to 3 indicates that the area of the watershed has a moderate drainage pattern, and if the value is less than 1, the area of the watershed has poor drainage. The DD analysis can be calculated from Equation 6 (Horton 1932):

$$DD = \frac{\sum Ls}{A} \quad (6)$$

Where, L_s is the sum of all river basin lengths and A is the total watershed area (km^2).

The Infiltration Number (IN) is the result of the DD and SF analysis of the watershed studied. IN is directly proportional to runoff (Faniran 1968; Das and Mukherjee 2005; Joji et al. 2013; Elewa et al. 2016). As the IN of the watershed shows high, the runoff remains high; and low infiltration number means the runoff is low. The IN analysis can be calculated from Equation 7:

$$IN = DD * SF \quad (7)$$

The additional physical factors applied in this study were mean annual precipitation, geology, soil, and distance to stream (Fig. 4). Mean annual precipitation factors were analyzed using data from the Thai Meteorological Department (TMD) from 2005-2020 to determine average rainfall, then spatial analysis using inverse distance weighted interpolation technique in spatial analysis tools in ArcGIS 10.2 software. The geology and soil variable data as nominal data were converted to raster data format. The distance to stream variable data were analyzed for distance from waterways using the Euclidean distance technique in spatial analysis tools.

The geology, soil, and land-use data are a nominal scale and is represented as categorical as float-number data as follows:

Geology data in the study area consisted of Phu Kradueng formation (Jpk) equal to 1, Phra Wihan formation (JKpw) equal to 2, Sao Khua formation (Ksk) equal to 3, Phu Phan formation (Kpp) equal to 4, Khok Kruat formation (Kkk) is 5, Maha Sarakham formation (KTms) is 6, and Quaternary fluvial deposits (Qa) is 7, according to the Department of Mineral Resources classification criteria.

Soil data in the study area consisted of slightly gravelly sand, coarse sand, loamy coarse sand, loamy fine sand, clay loam, clay, salinity soil, and marl soil. The two types of soils have different drainage potentials as shown in Fig. 4c, thus being represented as 1 and 2. Poorly drained soils are represented as 1 and well drained as 2, according to the classification criteria of the Land Development Department (LDD).

As for the land-use data, the study area has a variety of land uses, so it has been reclassified as follows: Agricultural land represented as 1, Forest land represented as 2, City and village represented as 3, Waterbodies represented as 4, and Miscellaneous area (including grass land, wetland, mineral, and salt pan) represented as 5, according to the classification criteria of the Land Development Department (LDD).

Land-use, distance to village, and distance to road are examples of key socioeconomic factors that affect flooding (Fig. 5). Land-use data is nominal data obtained from the Land Development Department (LDD). The data were converted to a raster data format, and the distance to village and distance to road variable data was obtained by analyzing distance from waterways using the Euclidean distance technique in spatial analysis tools.

Statistical approach

From the sequence of flood prone area analysis and spatial database analysis of driving factors, it was necessary to find factors affecting flooding in order to determine the flood context in LKCW, 17 variables were analyzed including elevation, slope, aspect, SPI, STI, TRI, TWI, SF, DD, IN, Mean annual precipitation, geology, soil, distance to stream, land-use, distance to village, and distance to road. These variables were analyzed together with flood prone area data using LR.

LR is a technique for discovering the empirical relationships between a binary dependent and several independent categorical and continuous variables (Nandi et al. 2016; Tehrany et al. 2017; Kim et al. 2020; Cao et al. 2020). LR is calculated using the following Equation (8).

$$Log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \ldots \beta_n x_{n,i} \quad (8)$$

Where, P is the flood prone area, x_i are independent variables and β is the coefficient value.

This statistical method was used to provide the variables that were analyzed to determine which variable had an influence on flooding in that area. It shows the effect of the variable in the β value, to determine the factor affecting the amount of flooding. These statistical principles consider the underlying and dependent variables for all grid cells in the LKCW area. In the conclusion, spatial data obtained from those Logistic regressions can be used to predict flood risk areas in the LCKW area by performing a classification method into 5 classes: very high, high, moderate, low, and very low. It is expressed as Flood Susceptibility Mapping to determine the area that should be addressed in a timely manner for flood disaster management for sustainable spatial development in the future.

RESULTS

Flood Prone Area during 2005–2021 in LKCW area

The flow system in dendritic-parallel drainage pattern of LKCW can divide the branch stream into two banks, on the left side and on the right side of the Lam Khan Chu stream. On the left side are the branch streams Huai Wang Kuang stream, Huai Sai stream, Huai Hoep stream and a short stream that flows into Bueng Lahan swamp. The important right-bank branches of Lam Khan Chu stream are Lam Sisiat stream, Huai Wang Ta Lat stream, Huai Dak Tat stream, Huai Muang stream, Huai Khlong Phai Ngam stream, Huai Khlong Lam In and short streams that flow into Bueng, Lahan swamp. The study of flooding area that occurred during August to October 2021 as Tropical Storm Dianmu hit Thailand, resulting in rainfall that exceeds the water-resistance area, causing overflow in the Lam Khan Chu reservoir. It partially damaged the reservoir, causing massive water inflows to flood the downstream areas, damaging the Bamnetnarong district and Chaturat district covering up to 112.067 km^2 (6.47% of the LKCW area) (Fig. 6a.). Although the flooded area is a narrow area along both banks of the Lan Khan Chu stream, Huai Khlong Phai Ngam, and Huai Khlong Lam In, but it has caused great damage to the area in the city, as most of them are community areas, economic and commercial areas, government offices, and agricultural areas.

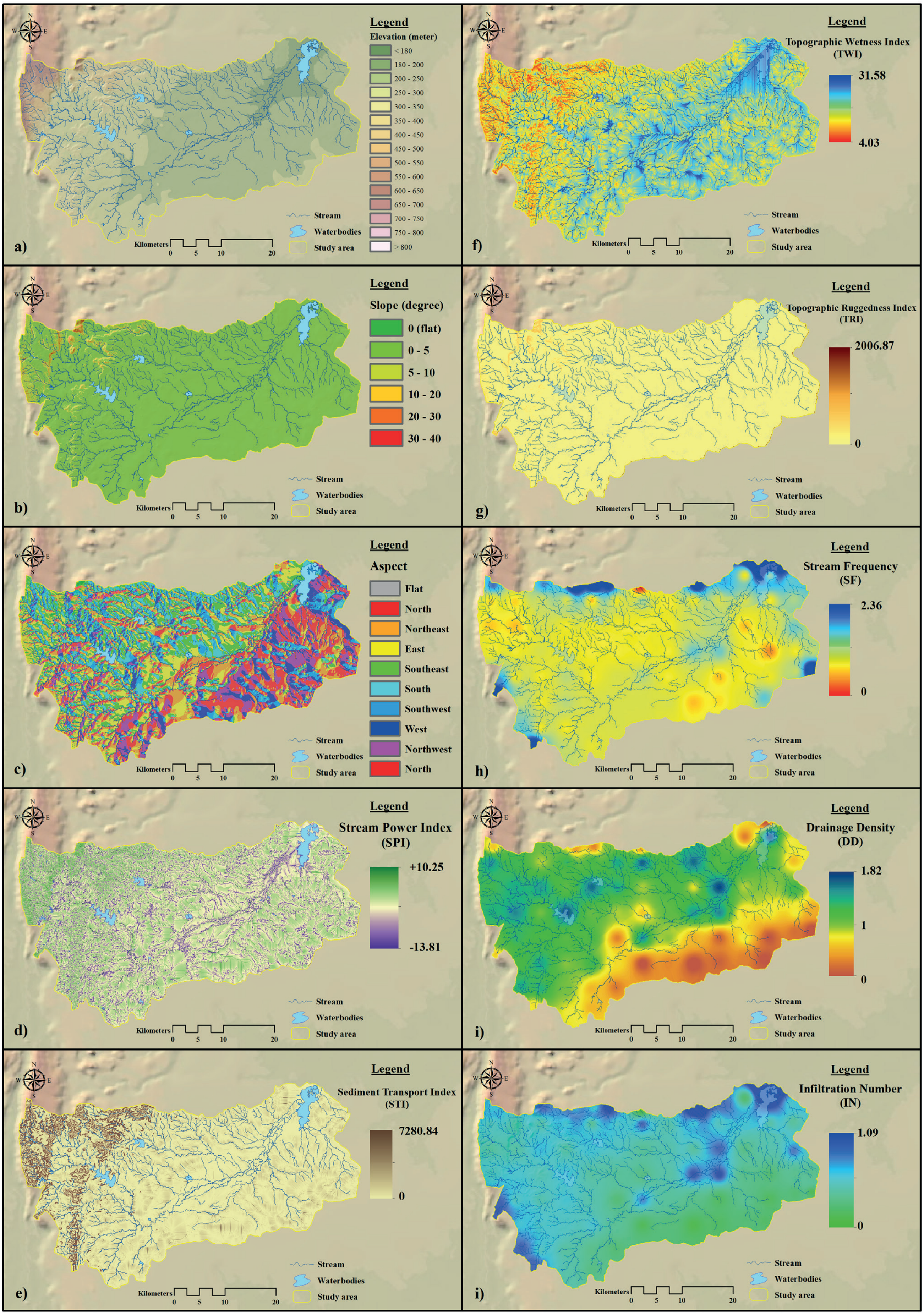

Fig. 3. Spatial database analysis of physical driving factors: elevation (a), slope (b), aspect (c), SPI (d), STI (e), TWI (f), TRI (g), SF (h), DD (i), and IN (j)

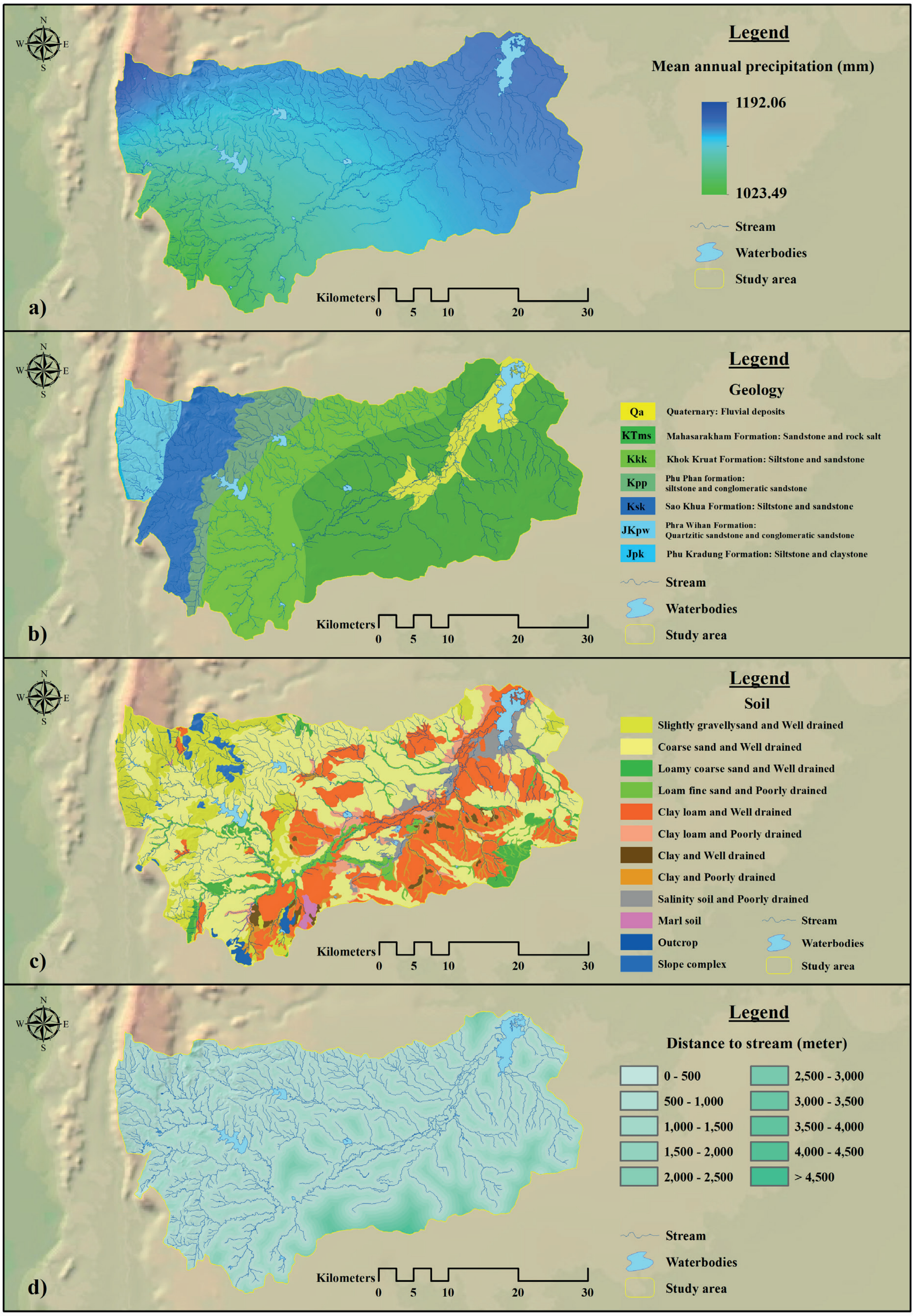

Fig. 4. Spatial database analysis of physical driving factors: mean annual precipitation (a), geology (b), soil (c), and distance to stream (d)

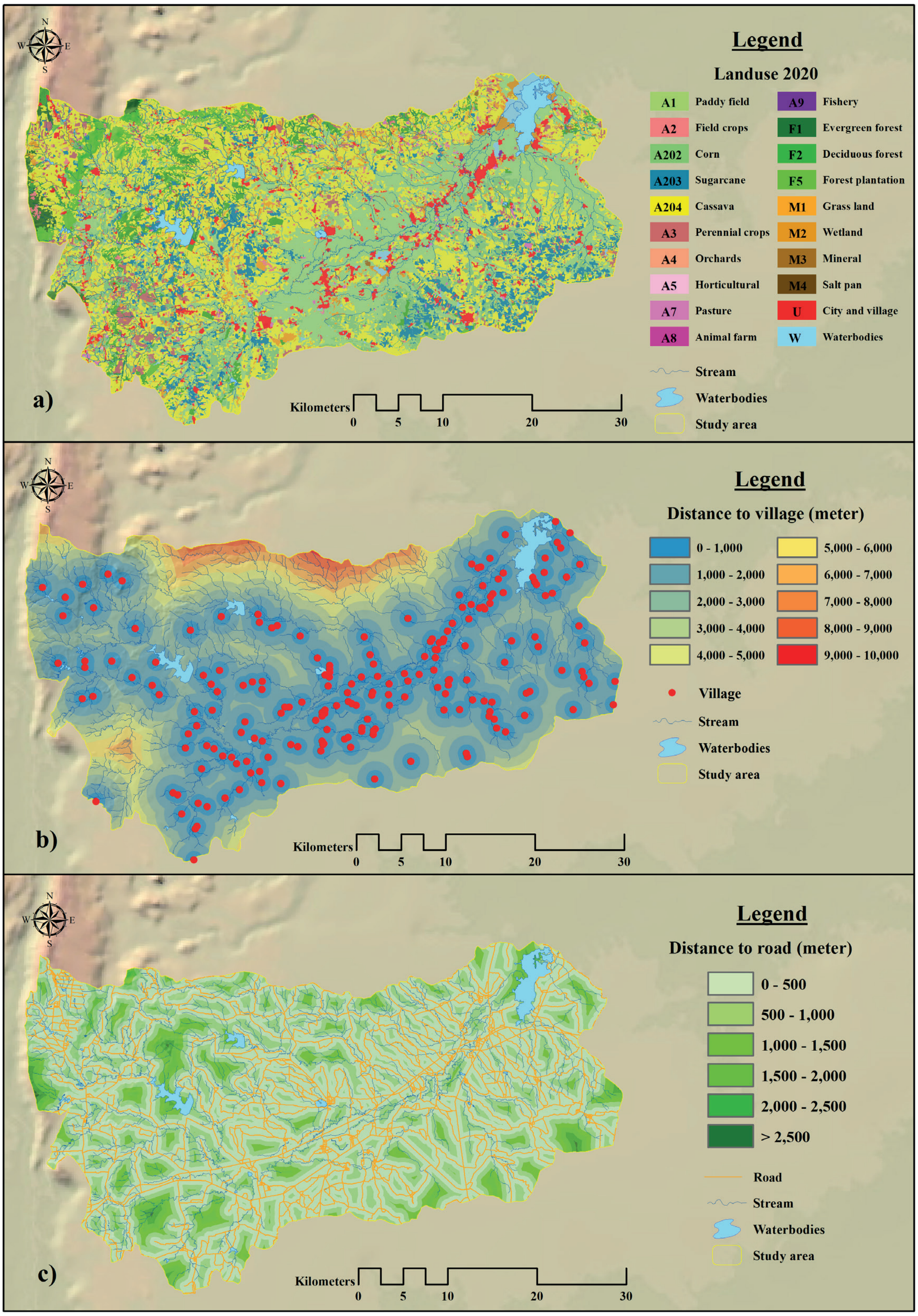

Fig. 5. Spatial database analysis of socio-economic driving factors: land-use (a), distance to village (b), and distance to road (c)

The area has undergone 11 frequent floods since 2005, according to the results of the flood prone area research conducted in LKCW between 2005 and 2021. 2017 was the year when flooding covered the LKCW the most, 127.252 km^2 (7.33% of the total watershed), followed by 2006, found that the flood area covered 118.054 km^2 (6.81 % of the total watershed area), and the years that no flood areas were found in the basin were 2005, 2011, 2015, and 2018, showing the proportion of flooded areas as shown in Table 2. The study of repeated flooding during 2005 – 2021 in LKCW found that most of the repetitive flooding areas occurred in the southern part of the Bamnetnarong district and continued northeast to Chaturat district and Bueng Lahan swamp. These areas are the main waterways of the LKCW area, namely Lam Khan Chu stream and Huai Khlong Phai Ngam, which flow patterns are braided streams, resulting in floodplain landscapes and therefore frequent flooding. As for the repeated flooding area, occurring 11 times in 17 years, it was found that an area of up to 0.543 km^2 (Table 3) appeared around Bueng Lahan swamp, which is northeast of Chaturat district, because it is a lowland terrain where many tributaries flow to the area (Fig. 6b).

Table 2. Flood Prone Area during 2005 – 2021 in LKCW

Year		2005	2006	2007	2008	2009	2010	2011	2012	2013
Area	km^2	-	118.054	68.846	22.327	16.139	101.531	-	11.087	78.854
	%	-	6.81	3.92	1.27	0.92	5.83	-	0.63	4.50
Year		2014	2015	2016	2017	2018	2019	2020	2021	
Area	km^2	10.986	-	82.768	127.252	-	5.370	17.025	112.067	
	%	0.57	-	4.73	7.33	-	0.31	0.98	6.47	

Table 3. Repeated flooding area over a period of 15 years (2005-2021) in LKCW

Repeated flooding (Time)	1	2	3	4	5	6	7	8	9	10	11
Area (km^2)	125.414	64.875	27.919	20.523	16.591	14.445	8.701	5.782	3.298	3.884	0.543

Factors affecting flooding in LKCW area

From the analysis of 17 key variables for determining the susceptibility to flooding in the LCKW area, were analyzed using the LR statistical process and the spatial database variables affecting flooding, the results of the study are shown in Table 4. The results were shown by statistical value β. If the β value of the variable was positive, the higher the variable, the more susceptible to flooding. But if the β value of that variable shows a negative value, it means that the variable with a lower value is more susceptible to flooding. The relative operating characteristic (ROC) shows how the regression equation can be used to predict flood prone risk area based on probability. The ROC values obtained for the probability of flooding area and non-flooding area are 0.899 and 0.865, respectively (Fig. 7), indicating a high value, because a value approaching 1.00 indicates that all 17 variables are effective in analysis of flood prone areas.

All variables were significant at the $p < 0.01$ entry and $p > 0.02$ removal levels (ROC relative operating characteristics)

Table 4. Logistic regression analysis of the flood prone area and affecting factors in LKCW area

Variable	Flooding area		Non-flooding area	
	Coefficient β value	Coefficient Exp β value	Coefficient β value	Coefficient Exp β value
Elevation (digital elevation model-DEM)	-0.032	0.968	0.041	1.040
Slope	-	-	0.018	1.018
Aspect	-0.001	0.999	0.001	1.001
Stream Power Index (SPI)	-0.079	0.924	0.079	1.082
Sediment Transport Index (STI)	-	-	-	-
Topographic Ruggedness Index (TRI)	-	-	-	-
Topographic Wetness Index (TWI)	0.042	1.043	-0.051	0.969
Stream Frequency (SF)	0.795	2.214	-0.785	0.442
Drainage Density (DD)	-0.786	0.456	0.796	2.195
Infiltration Number (IN)	-	-	-	-
Mean annual precipitation	-0.014	0.986	0.014	1.014
Geology	0.845	2.327	-0.855	0.430
Soil	-0.629	0.533	0.639	1.875
Distance to stream	-0.0002	1.000	0.0002	1.000
Land-use	-0.067	0.935	0.067	1.069
Distance to village	-0.001	0.999	0.001	1.001
Distance to road	0.0001	1.000	-	1.000
Constant	20.908		-20.875	
The relative operating characteristic (ROC)	0.899		0.865	

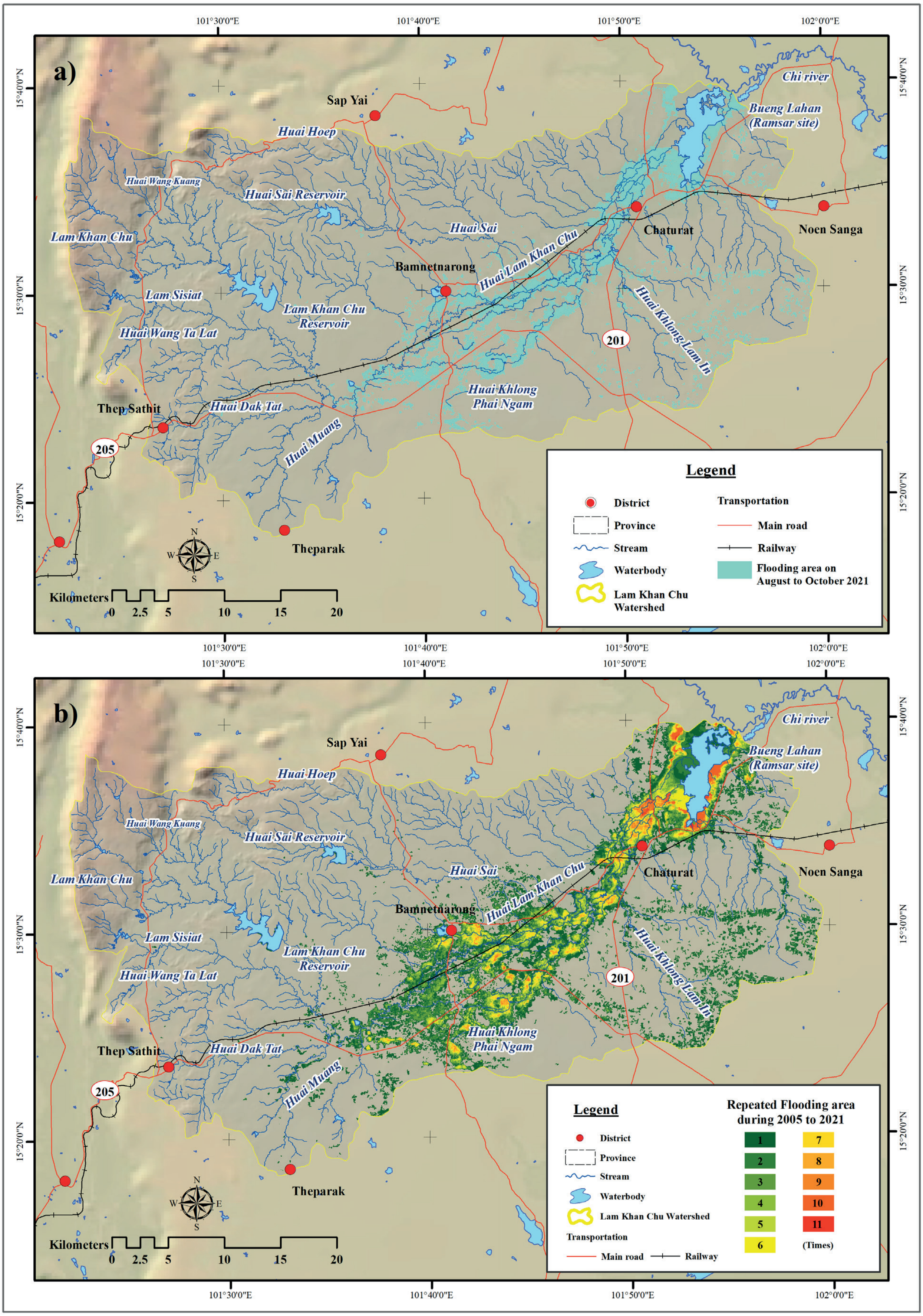

Fig. 6. Flooding area on August to October 2021 in LKCW area (a) and Repeated flooding area during 2005-2021 in LKCW area (b)

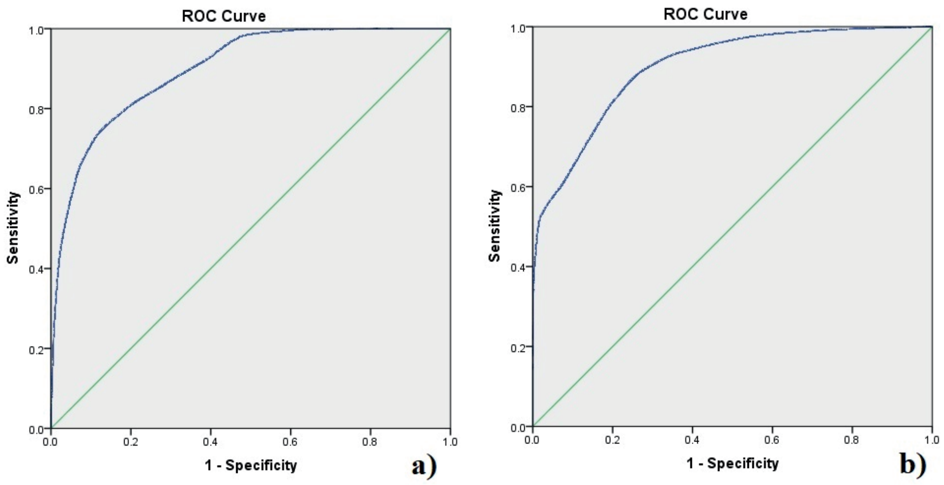

Fig. 7. The relative operating characteristic (ROC) value: flooding area (a) and non-flooding area (b)

The results showed that the flooding area had 4 variables showing high positive β value, namely geology, SF, TWI, and distance to road, respectively. For the variables showing high negative β value, there were 9 variables, namely DD, soil, SPI, land-use, elevation, mean annual precipitation, aspect, distance to village, and distance to stream, respectively. There were 4 variables that did not affect the flooding area in the LKCW area: slope, STI, TRI and IN.

The main reason that four variables (slope, STI, TRI, and IN) did not show β values after logistic regression analysis was due to the physical topography of the study area being largely flat. Only steep slope appeared in a small amount of watershed in the western part of the study area, making slope and TRI variables not statistically significant.

STI levels in the study area were very low, covering the middle and lower parts of the watershed, showing that sediment-carrying was seldom present in the study area. Because there are two important reservoirs, Lam Khan Chu Reservoir and Huai Sai Reservoir, which are sediment banks. In addition, the tributary streams are small and short streams, causing the water mass to not have enough strength to erode the channel until sediment occurs along the waterway, so it is not statistically significant.

As for IN, moderate to low values are found in the area, where IN values are low means, the runoff is low. This is because in the study area there is topography with low potential to store water in the form of surface water. Because most of the waterways are perennial streams, causing them to seep into the ground and collect in the form of groundwater layers, making the IN value not statistically significant.

The flooding area occurred mainly from geology and SF variables, both of which showed high positive β values at 0.845 and 0.795, respectively. It shows that the flooding area is mainly caused by physical factors, as the topography of the LCKW area is supported by soft sedimentary strata, especially modern quaternary sedimentary rocks formed by fluvial deposits. In addition, the area is a low-lying area, resulting in large volumes of water being stored in the area. Most of the LCKW area is also covered by the Mahasarakham Formation, which consists of sandstone and rock salt, soft shale geologic, submerged sedimentary region secondary to Quaternary Neolithic sedimentary rock. The SF variables were the results obtained from the analysis considering the 1st order waterways in the watershed. The SF high value represents an area where the low runoff of the river is defined as the slow flow of water in the river from upstream to downstream over a long period of time, the greater the flooding in the lowland areas for a long time. It can be seen that a high SF value of 2.36 appeared in the surrounding Bueng Lahan swamp. The TWI variable is a predictive index of water accumulation in a watershed area. A high TWI value indicates an area prone to accumulation of water in a basin, making it more prone to flooding in an area. The TWI level shows a high of 31.58 visible on both sides of the main river. High TWI levels can be observed in the vicinity of the Bueng Lahan marsh, the Huai Lam Khan Chu stream, the Huai Sai stream, the Huai Khlong Phai Ngam, and the Huai Dak Tat. As for the distance to road variable, flood-affected areas tend to be far from transport routes.

For variables showing high negative β values affecting flooding area, it can be seen that DD and soil variables showed high negative β values at -0.786 and -0.629, respectively. It shows that the flooding area is mainly caused by physical factors as well. In particular, the DD variable, which was found to be moderate to less than 1, indicates a moderate to low level of drainage. It shows that flood-prone area conditions, especially in the southern and central lowlands of the LKCW area. As for soil variables, the high negative β value was found at the secondary level. The results showed that most of the soil conditions are poorly drained soil found in salinity soil, loam fine sand, and clay loam. As a result, the water volume cannot be drained effectively underground. The SPI variable shows the negative β value as well. It can be seen that the area where the low SPI value found is on both sides of the mainstream where flooding occurs. The land-use variant, floodplains mainly occur in agricultural and lowland areas. Elevation, distance to village, and distance to stream were the three variables that were found to have low negative β values. It represents an area with low elevation of terrain that is susceptible to flooding, including areas near villages and stream.

The results of the study in the non-flooding area consisted of 9 variables showing high positive β value: DD, soil, SPI, land-use, elevation, mean annual precipitation, aspect, distance to village, and distance to stream, respectively. There were four variables showing high negative β value, namely geology, SF, TWI, and distance to road, respectively. It can be seen that it is the reverse of the factors affecting the previous flooding. There are also four variables that do not affect the non-flooding area in the LKCW area: slope, STI, TRI and IN. The results of all variables that were indicators for the occurrence of flood prone areas were subsequently analyzed on the flood susceptibility map in LKCW to form a spatial database for effectively managing flood risk areas.

Flood susceptibility map in LKCW area

The results of the study of flood prone risk area in LCKW by statistical analysis of LR, using the β value as a database and creating a map for disaster management at the watershed level to show it as a flood susceptibility map in LKCW area (Fig. 8) was analyzed spatial using GIS as shown in Equation 9.

$$\begin{aligned}Y = 20.098 &+ (-0.032 * \text{“}Elevation\text{”}) + (-0.001 * \text{“}Aspect\text{”}) \\ &+ (-0.079 * \text{“}SPI\text{”}) + (0.042 * \text{“}TWI\text{”}) + (0.795 * \text{“}SF\text{”}) \\ &+ (-0.786 * \text{“}DD\text{”}) + (-0.014 * \text{“}Mean\ annual\ precipitation\text{”}) \\ &+ (0.845 * \text{“}Geology\text{”}) + (-0.629 * \text{“}Soil\text{”}) \\ &+ (-0.001 * \text{“}Distance\ to\ stream\text{”}) + (-0.067 * \text{“}Land\ use\text{”}) \\ &+ (-0.001 * \text{“}Distance\ to\ village\text{”}) + (0.001 * \text{“}Distance\ to\ road\text{”})\end{aligned} \quad (9)$$

The β value of the variables made the findings a highlight of this study, as it was able to show the level of risk as spatially appropriate data based on the variables involved and affecting specific flooding in the LKCW area. Results of the flood susceptibility study show that flood susceptibility areas are classified into 6 levels: Very high, High, Medium, Low, Very Low, Non-flooding susceptibility respectively (Table 5). A very high flood susceptibility level is discovered in the LKCW region, spanning up to 148.308 km^2 (8.566% of the total area). They appear mainly in the surrounding areas of both main rivers from the downstream to the middle stream of the watershed, especially around the Bueng Lahan swamp and the Huai Lam Khan Chu stream, Huai. Khlong Phai. Ngam, and Huai Muang. The water feature is Braided stream and the terrain is floodplain which makes the area prone to flooding, thus making it a very high level of flood susceptibility. High-risk areas and moderate-risk areas appear close to the very high level of flood susceptibility area as well, but far from the main stream. It covers an area of more than 247.421 km^2 (14.291%) and 310.414 km^2 (17.930%), respectively. The low-risk area, covering an area of 271.594 km^2 (15.687%), was found in the Huai Lam Khan Chu stream, including Huai Khlong Lan In, Huai Khuean Lan, Huai Sai, Huai Wang Ai Pho, Huai Wang Ta Lat, and Huai Dak Tat. Most of the above areas are upstream of the LKCW area. The very low-risk area covers most of the LKCW area, up to 725.153 km^2 (41.885%). Nearly half of the watershed is prone to flood disasters at very low levels, but the likelihood is relatively low. Most of them are upstream of secondary waterways in the northern region, south and west of the basin. Non-flooding susceptibility, appearing in the Northwestern region of the LCKW area, is 28.399 km^2 (1.640% of the total area) considered to be non-flooding susceptibility. Mountainous area can be found in Pa Hin Ngam National Park, a significant watershed forest area in the research area.

DISCUSSION

Floods can be caused by a number of factors and future major floods cannot be accurately predicted (Khosravi et al. 2016). Therefore, it is imperative to collect as many variables affecting flooding as possible, and to select an analysis model that is consistent and timely in response to future flood disasters. It can be seen that from this research, we have tried to select factors that affect flooding, i.e., physical factor and socio-economic factor, with 17 variables related to flooding in the LKCW area as follows: elevation, slope, aspect, SPI, STI, TRI, TWI, SF, DD, IN, mean annual precipitation, geology, soil, and distance to stream. Land-use, distance to village, and distance to road. All 17 variables were created in a geo-database for analysis along with actual flooding area data. The data is then analysed in a geographic information system (GIS) to assess flood susceptibility assessment in the LKCW area. Finally, a flood susceptibility map was created, yielding satisfactory and reliable results, which can be used as a geospatial database for decision-making for flood risk management.

The study of recurrent flooding in the LKCW area yielded interesting data. Over the past 17 years, GISTDA data on flooding from 2005 to 2021 found that 11 recurrent flooding areas occurred mainly in the central region and continued to outlet area, surrounding Bueng Lahan swamp, northeast of the study area, especially the main waterways such as Lam Khan Chu stream and Huai Khlong Phai Ngam stream. The terrain is floodplain with a vast marshland and a braided stream system. Therefore, the area is prone to repeated flooding. This is consistent with the results of a study by (Izumida et al. 2017), studied the repeated flooding area in the Kinu river, Central region in Japan by applying UAV-SfM photogrammetry and aerial lidar to assess the damage caused by flooding. The Piave River in Italy also found that the landscape of the basin was a braided river. It is similar to the floods in the Piave River in northern Italy, which appear braided rivers with strongly impacted flow and sediment regimes (Ziliani et al. 2020). Like the results of a study by (Rajbanshi et al. 2022) in the braided Brahmaputra River in Assam, India, it was found that the 2019 major floods in the Brahmaputra River affected sediment changes in the river, whether it is the movement or accumulation of sediments in the river. It can be concluded that watersheds with floodplain morphology and braided river systems tend to experience repeated flooding almost every year. The communities and agricultural areas in these areas are often affected by floods.

Factors affecting flooding in LKCW area were analysed using LR statistical process. The results showed that

Table 5. Flood susceptibility area in LKCW area (km^2)

Flood susceptibility level	Area	
	km^2	%
Very high	148.308	8.566
High	247.421	14.291
Medium	310.414	17.930
Low	271.594	15.687
Very Low	725.153	41.885
Non-flooding susceptibility	28.399	1.640
Total	1731.289	100.000

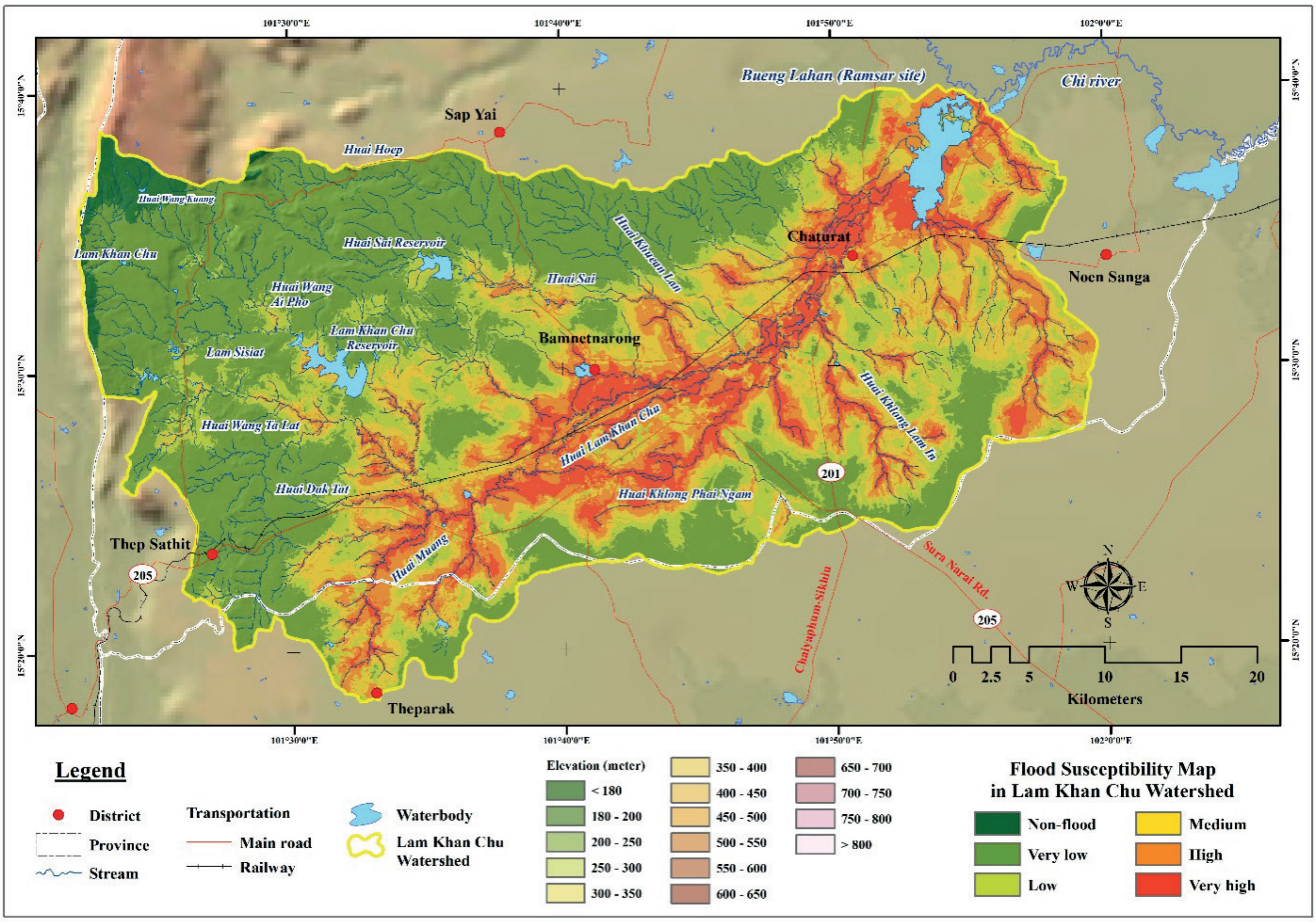

Fig. 8. Flood susceptibility map in LKCW area

the physical factor variables were the most important flooding probability indicators. Specifically, a study in the LKCW area found that geology and SF variables showed high positive β values at 0.845 and 0.795, respectively. Meanwhile, DD and Soil variables showed high negative β values at -0.786 and -0.629. respectively. Geological conditions are supported by an important sedimentary rock group, the Korat group. The rocks of the Jurassic to Cretaceous period are Phra Wihan formation, Sao Khua formation, Phu Phan formation, Khok Kruat formation, and Maha Sarakham formation, respectively (Rattana et al. 2022). Alluvial deposits in the Quaternary era were the most susceptible variables to flooding in the study area, as soft rock contributes to the erosion of water systems on the terrain surface (Prasanchum et al. 2022). Those are located in the valley bottoms which are most prone to flooding in terms of relative elevation. This creates a cuesta topography landscape with steep edges in the west and gradually slopes to the east, resulting in a dendritic-parallel drainage pattern i.e., several tributaries such as Huai Muang, Huai Dak Tat, Huai Wang Ta Lat, LamSisiat, Huai Wang Ai Pho, Huai Sai, Huai Khuean Lan and the short streams surrounding Bueng Lahan flow to the main line, Huai Lam Khan Chu stream. In addition, the SF variables in the study area show the SF high value, indicating the area where the low runoff is the flow of water in the river from the upstream area to the downstream area moving slowly, causing enormous volumes of water flooded in Huai Lam Khan Chu stream for over a month. The DD variable found at a moderate to the level less than 1, showing a moderate to low level drainage system, indicating that the area is prone to flooding, especially in the southern and central lowlands of the LCKW area. The soil variable found a high negative β value at a lower level. The results showed that most of the soil conditions were poorly drained soils found in Salinity soil, Loam fine sand, and Clay loam, which were more consistent with the results of the SF and geology variables. It can be seen that the results of the study in the LKCW area revealed different variables that affect the susceptibility to flooding from other areas. As a case study of (Tehrany et al. 2017) of flood susceptibility mapping in the Xing guo area, China, it was found that the slope variable was the most important variable affecting the top susceptibility to flooding, as did (Al-Juaid et. al. 2018) found high logistic regression coefficient values for Topographic slope variable as high as 1.0483. (Cao et al. 2020) studied flood susceptibility from the Fujian Province, located in south-eastern China, and found that the top influencing variables were land-use and topographic relief. Unlike this study, it was found that the slope variable did not show the coefficient β value in the LKCW area, since most of the area, more than 80 percent, has a low slope of 0–5 degree, but other physical variables that affect susceptibility to flooding were found, including geology, SF, TWI, DD, soil, and SPI, which showed high β value coefficients. In summary, the overall picture from the discussion results shows the difference of factors affecting flooding. It is evident that the LKCW area has different topography and geomorphology from other areas, resulting in β value coefficient of the variables studied changes according to the physical characteristics of the area. Therefore, flood susceptibility studies in other areas should be aware of the causal factors to be studied first in the study of flood risk areas.

Flood susceptibility mapping, that has been generated after obtaining a flood susceptibility variable in the LCKW area, can be indicated sensitivity into 6 levels. It was found that 8.566% of the study areas showed a very high flood susceptibility level, and 14.291% of the study areas showed a high flood susceptibility level. It can be seen that one-fifth of the basin is at high risk of flooding, particularly in the surrounding areas of Bueng Lahan swamp, Huai Lam Khan Chu stream, Huai Khlong Phai Ngam, and Huai. Muang. It should be especially vigilant if being in the Inter-tropical convergence zone or a tropical cyclone moving into the watershed area, because of the physical nature of the area that is a large basin with slow drainage. For this reason, flood susceptibility mapping is therefore essential, in order for people in the area to understand the spatial context, to understand the geography and limitations of the area, especially at the community and local level that still have the limited capacity to cope with disasters and be prepared to cope and reduce the loss of life and property of people in the LKCW area in the event of the next major disaster.

CONCLUSIONS

Flooding is a catastrophic event that occurs almost every year during Thailand's monsoon season and is particularly severe during the tropical cyclone moving into the area, especially in the watershed areas of northeastern Thailand where this problem is often encountered. This research aims to solve the problems and mitigate such impacts by analyzing individual factors to find answers to the causes of flooding in the study area, by using logistic regression analysis together with GIS to create a Flood susceptibility mapping in LKCW. The results of the study identified important variables affecting flooding including geology, SF, TWI, DD, soil, SPI, land-use, elevation, mean annual precipitation, aspect, distance to road, distance to village, and distance to stream. All such variables are represented by the β value coefficient, which is analyzed to create a flood susceptibility mapping in LCKW. Recommendations for physical research in the basin where high-resolution DEM data can clearly detect the physical characteristics of the stream channel. Stream channel gradient and stream channel depth/width ratio should be added. This research shows that the utilization of flood prone risk map is a useful basis in taking preventive actions to mitigate floods, and relevant agencies should be expedited to assist the most vulnerable areas to mitigate floods. Also, planning and preparing for future floods in high- to very high-risk areas in the LKCW area must be performed. However, this risk map is suitable for alluvial terrain. If used in other areas, other relevant factors should be examined, including the flood context, to make logistic regression analysis more effective.

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