FLOOD PRONE RISK AREA ANALYSIS DURING 2005 - 2019 IN LAM SE BOK WATERSHED, UBON RATCHATHANI PROVINCE, THAILAND

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ABSTRACT:
This research investigates the application of logistic regression analysis for flood prone risk mapping in the Lam Se Bok watershed area. The study found that floods have occurred as many as 15 times since 2005. In 2019, flooding covered 200.01 km^2 of the watershed (5.51% of the total watershed). Among the areas that flood every year, 15 floods occurred in the lower part of the LSBW basin in Na Udom village, Khok Sawang and Fa Huan village, Rai Khi sub-district, which are in the south of Lue Amnat District, Amnat Charoen Province, as well as in parts of Dum Yai sub-district, Muang Sam Sip district, Ubon Ratchathani. Logistic regression analysis was used to determine the influence of certain variables on this flooding. The variables showing positive β values were mean annual precipitation and distance to a road. The variables showing negative β values included elevation, terrain, slope, soil drainage, distance to stream, land-use, and distance to village, respectively. All of these variables can be analyzed for their Flood Prone Risk area in GIS. The study found that flood-prone areas at the very high-level flood prone risk areas, with a total area of 638.59 km^2 (17.59%), high level flood prone risk areas cover an area of 1,848.10 km2 (50.92%). Medium flood prone risk areas cover 794.95 km2 (21.90%). Low flood prone risk areas cover 310.86 km2 (8.56%), the least vulnerable to flooding encompassed 46.35 km2 (1.27%)., and occurred in areas with low elevation and areas with high annual average rainfall when the variable was located in the middle and downstream parts of the LSBW river basin.

Key-words: *Flood prone, Flood Risk Analysis, Lam Se Bok Watershed, Ubon Ratchathani*.

1. INTRODUCTION

Floods are a frequent problem and occur annually in watershed areas. Factors affecting flooding often include heavy rains over a long time period, since the monsoon troughs run across this watershed area (Papaioannou et al., 2015; Şarpe & Haidu, 2017; Cabrera & Lee, 2020). Terrain with inefficient drainage is also one of the top factors affecting flooding, such as a river with a large amount of sediment, a curved river with few branches, etc. Besides the physical factors, socio-economic factors are also contributing factors that accelerate more frequent flooding (Geist & Lambin 2002; Luo et al., 2010; Lambin & Meyfroidt 2010). These factors inevitably cause changes in land use patterns, which is why it is important to study the context of such factors through flood prone risk area analysis (Waiyasusri & Chotpantarat, 2020).

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Thailand has flooded areas of 78,400 km^2, accounting for 15 % of the country. Lam Se Bok watershed (LSBW) is a sub-watershed of the Mun River Basin. The watershed area is in Amnat Charoen and Ubon Ratchathani province with a total basin area of 3,629 km^2, and annual floods are common when the monsoon season is reached (July - October of every year), causing a lot of agricultural land damage. The topography of Phu Sing-Phu Pha Phung Forest Park in Amnat Charoen Province is only that of a low hill with non-steep elevation gain, thus the ability to hold water is relatively low, although there are many tributaries in this basin, which also flood every year. The flood prone risk area analysis approach that has been used over the past decade analyzes flood prone area data at the watershed level, providing a very important dataset for watershed management (Kongmuang et al., 2020; Prasanchum et al., 2020). The information should be obtained from an accurate and efficient source in order to be used as a spatial database for Geo-informatics. The Radarsat-2, a Canadian natural resource satellite, is one of the top flood databases frequently used in flood disasters. It is effective in recording data with a Synthetic Aperture Radar (SAR) system in the C band spectrum, and can record flood data both by day and night (Singhroy, 1995; Baiocchi et al., 2014). This makes it possible for flood monitoring that efficiently monitors unusual high-water levels.

Different methods have been employed to describe flood prone risk areas using various stochastic methods with GIS and remote sensing. Nandi et al. (2016) studied cases of flooding in Jamaica during heavy rainfall from tropical storms and Atlantic hurricanes, revealing the related variables of local geology, geomorphology, hydrology and land-use. Tehrany et al. (2017) applied the principles of logistic regression to the analysis of flood susceptibility mapping in China. Their results revealed that the slope variable had a relatively high influence on flooding, making the slope variable one of the top priorities in the analysis of flood-prone areas. Lim and Li (2018) produced a study entitled “Flood Mapping Using Multi-Source Remotely Sensed Data and Logistic Regression in the Heterogeneous Mountainous Regions in North Korea”, it found that the DEM data for terrain analysis should be of high resolution. Chen et al. (2019) used a machine learning technique for flood mapping in the Yangtze River Delta, China, determining that the rainfall variable is important for model analysis and can also be a catalyst for flooding. On the other hand, Ma et al. (2019) also used Machine Learning Techniques in the Yunnan Province, China, but found that the Curve number (CN), surface runoff and interflow, which are related to the Soil drainage variable, were the primary variables. Variable data for the analysis of those factors requires important tools like GIS and remote sensing to be used for efficient spatial analysis, as with the Hossian and Meng (2020) integrated GIS and cartographic approach, which analyzed variables affecting flooding to determine the flood prone risk areas of Birmingham.

In this research, logistic regression analysis was applied in the analysis of flood prone risk areas using a spatial database that allowed for the construction of a flood prone risk area map in the LSBW. The study took into account the most important variables referred to by other studies to come up with a digital elevation model (DEM), which is widely used in terrain analysis (Barreca et al., 2020). DEM data can effectively generate the terrain and slope data of the watershed (Ahmad, 2018; Banerjee et al., 2017; Goulden et al., 2016). In addition, the main physical variables considered to be the highlights of flood risk analysis included the mean annual precipitation and soil drainage variables. Socio-economic factors that were relevant and provided information on flooding considered to be important variables that were used in these flood applications included: Land-use, Distance to stream, Distance to village, and Distance to road (Rama, 2014; Sujatha et al., 2015; Chandniha & Kansal, 2014). The use of these variables to quantify flood-associated attributes is a significant contribution to the current work. This study aims to find and predict the variables that have the greatest impact on flooding.

The key to solving spatial issues in watershed management to solve the problem of areas susceptible to flooding, guidelines for the flood maps on various planning structures should be established for protecting cultural landscape against flood risks, such as A Framework for Boosting Cultural and Natural Heritage Conservation in Central Italy (Dastgerdi et al., 2020). Sustainable solutions to flooding should be based on integrated community cooperation between researchers, local authorities and local communities, to gain a true local understanding of understanding of climate – weather – flood linkages. It is a bottom-up, vulnerability-based decision analysis frameworks, such as case studies in Tompkins County, New York, USA, and in various European areas as Flanders (Belgium), Niedersachsen (Germany) and Calabria (Italy) (Schelfaut et al., 2011; Knighton, et al., 2018).

The objective of this research was to analyze the recurrent flood prone risk areas in the LSBW, Amnat Charoen and Ubon Ratchathani Provinces during the period 2005-2019, and analyze the factors affecting such flooding in order to forecast them. By using logistic regression analysis as a guideline for planning and surveillance in the event of future floods, we prepared the data of the aforementioned study in a spatial database format for sustainable flood prone risk area management that may occur in the future.

2. STUDY AREA

LSBW is geographically located at latitude 15° 16' 26" N to 15° 57' 7" N and longitude 104° 30' 21" N to 105° 13 '44" N, with a total basin area of 3,629 km^2. The topography of the basin is in a dendritic drainage pattern (Strahler, 1964). The upstream area is in the north and northeast of the basin. This is a low hill with an altitude of 200-300 meters above sea level (msl) in Phu Sing-Phu Pha Phung Forest Park. The drainage system has the direction of water flow going from the northwest to the southeast. The major streams are the Huai Se Bok, Chan Lan, Phra Lao, Ta Thiao, Khulu, Saphue, and Wang Hai-Phang Ho-Yang, all of which flow into Lam Se Bok and into the Mun River at Tan Sum District, Ubon Ratchathani province (**Fig. 1**).

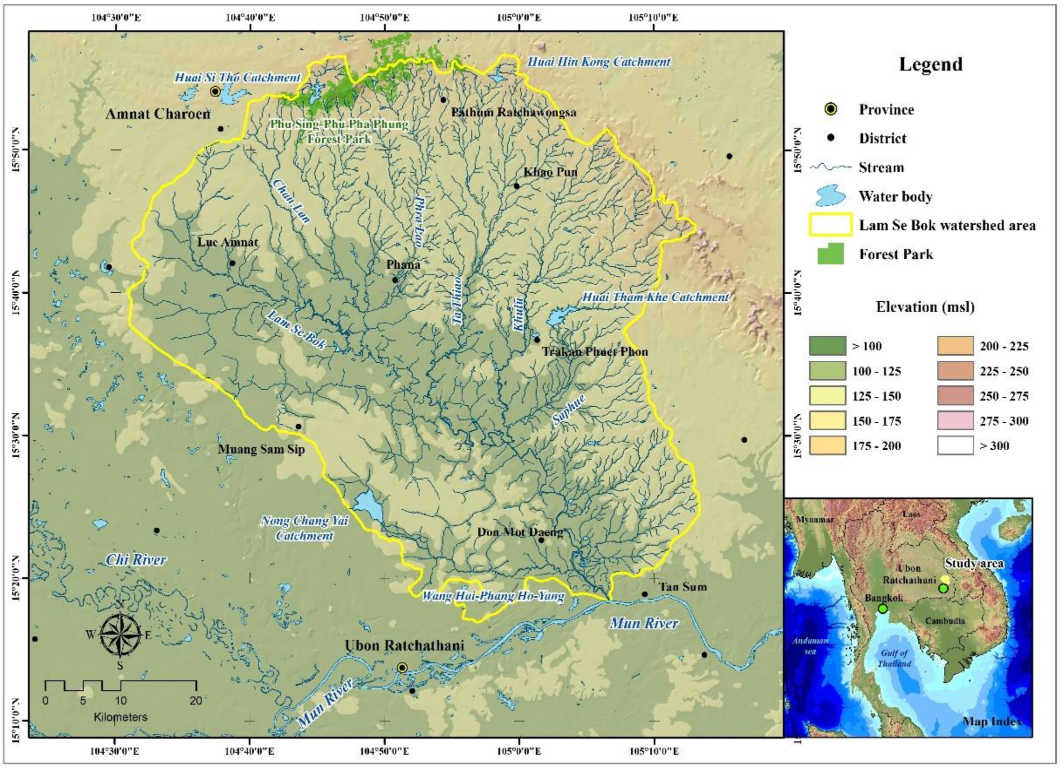

Fig. 1. Geographic map of the Lam Se Bok watershed area.

3. DATA AND METHODS

The methods for conducting this research consisted of analyzing recurring flood prone areas in LSBW, Amnat Charoen and Ubon Ratchathani Provinces, from 2005 to 2019, and analyzing the factors affecting flooding to forecast flood prone risk areas using a Logistic Regression analysis method. Data preparation is shown in **Table 1** and the research process is shown in **Fig. 2,** as follows.

Table 1.

Spatial data layers used in study.

Main themes	Year	Data preparation methodology
Actual flood area	2005-2019	Geo-Informatics and Space Technology Development Agency (public organization) (GISTDA)
Digital Elevation Model (DEM)	2014	Land Development Department
Terrain data	2014	Derived from the DEM
Slope	2014	Derived from the DEM
Soil drainage	2013	Land Development Department (LDD)
Mean annual precipitation	2005-2019	Interpolated from existing rainfall information from the observation stations of the Thai Meteorological Department (TMD)
Distance to stream	2013	Interpolated grid theme contains a Euclidean distance from the drainage system on spatial analysis. Derived from Department of Water Resource, Thailand
Distance to village	2013	Interpolated grid theme contains a Euclidean distance from the village. Derived from Royal Thai Survey Department (RTSD)
Distance to road	2013	Interpolated grid theme contains a Euclidean distance from the highway and road. Derived from Department of Public Works and Town & Country Planning.
Land use	2018	Land Development Department (LDD)

3.1. Flood Prone Area Analysis

The flood prone area was generated from actual flooded areas from 2005 to 2019 using overlay analysis tools in GIS, resulting in repeated flooding area data over the past 15 years. Then, the flood prone areas were analyzed in LSBW areas and those flood prone areas were analyzed for the next statistical logistic regression.

3.2 Affecting the Flood Risk Area using Logistic Regression Analysis

From the flood prone area analysis, it was necessary to search for the factors affecting the flooding to determine the flooding context in Lam Se Bok watershed. The factors analyzed included 9 variables: Elevation, Terrain, Slope, Mean annual precipitation, Soil drainage, Distance to stream, Distance to village, Distance to road, and Land use (**Fig. 3**). These variables were analyzed in conjunction with flood prone area data using logistic regression analysis.

Logistic Regression 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) .Logistic regression analysis is calculated using the following, Eq. (1):

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

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 and analyze the variables that influenced the flooding of the area. It will show the effect of the variable in the value of β, showing how much that factor affects the flooding in that area. The aforementioned statistical principle considers the preliminary and the variables for every grid cell in the LSBW area.

In conclusion, the spatial data obtained from Logistic Regression can be used to forecast flood risk areas in the LSBW area using a classification method utilizing 5 classes: very high, high, moderate, low, and very low. A flood prone risk area map is thus shown in order to obtain results highlighting the areas that should be urged to promptly resolve potential flooding disasters for sustainable spatial development in the future.

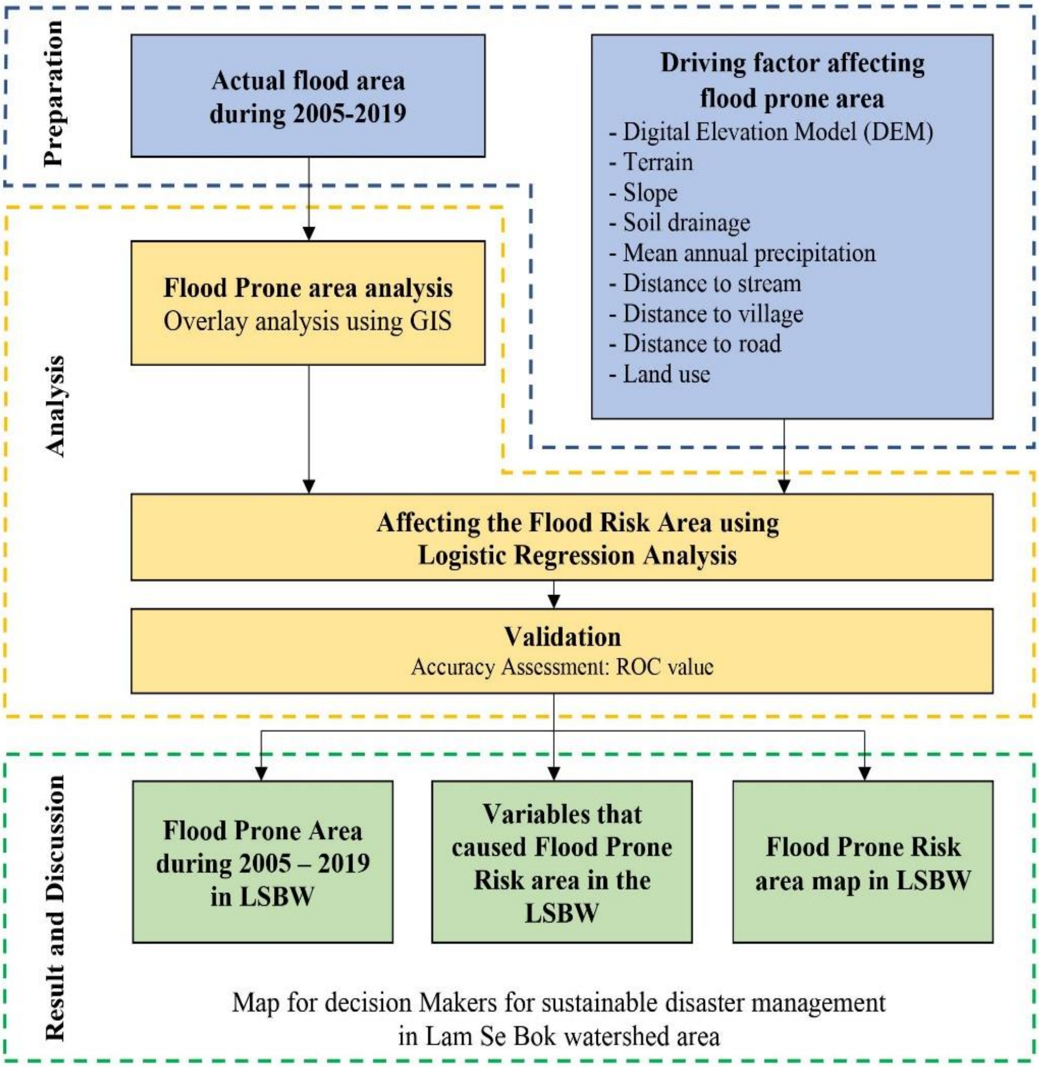

Fig. 2. Flowchart of the Research Process.

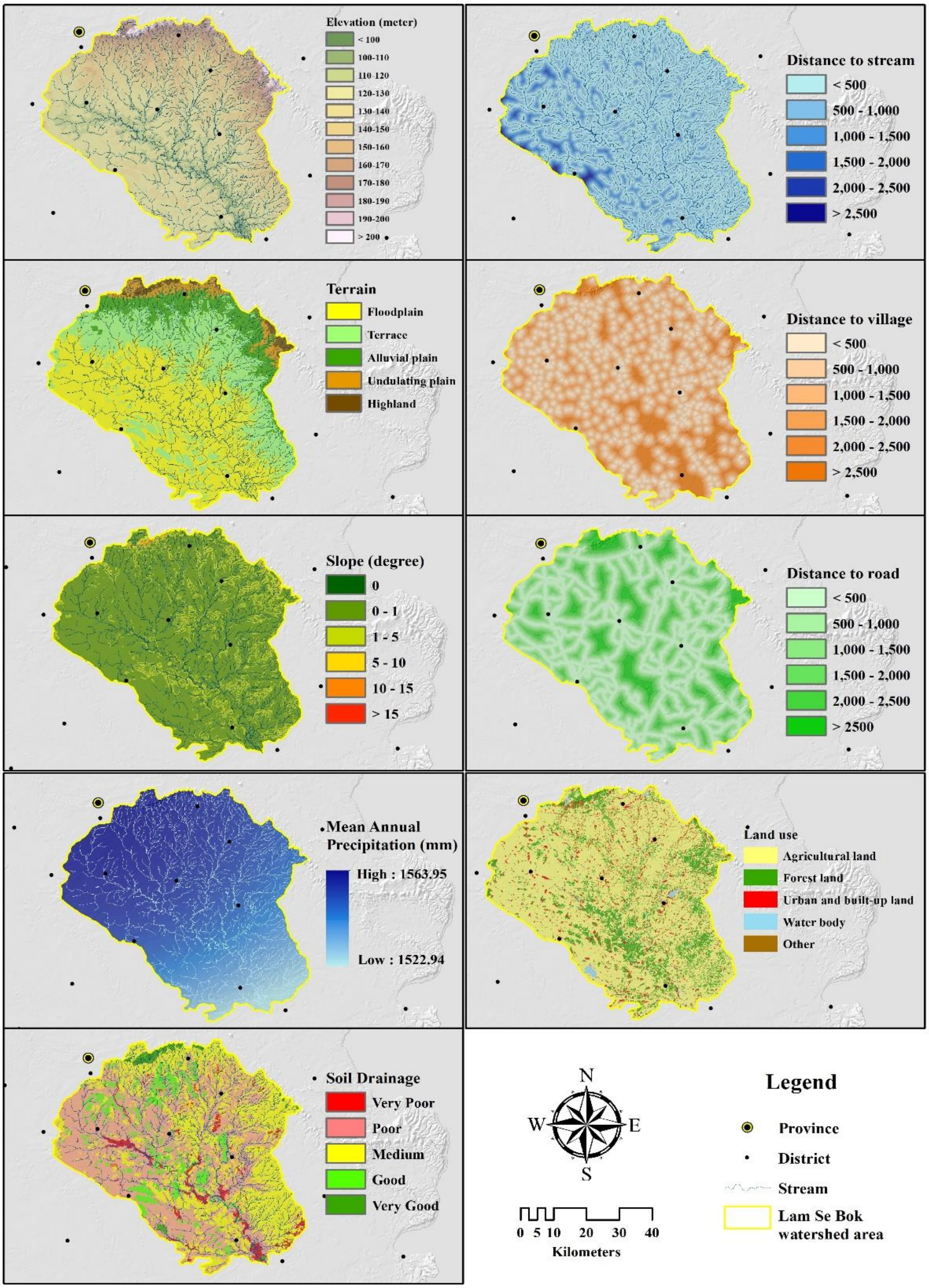

Fig. 3. Nine variables for the analysis of factors affecting flooding.

4. RESULTS AND DISCUSSION

4.1 Flood Prone Areas from 2005 ‑ 2019 in LSBW

LSBW is a tributary of the Mekong River Basin originating in Phu Sing-Phu Pha Pha Phung Forest Park. The flow pattern of the watershed is in a dendritic drainage pattern, creating a cumulative flow area from the middle to the downstream parts of the watershed. Results from the Flood Prone Area study during the 2005 - 2019 period in LSBW found that there have been as many as 15 frequent floods since 2005. In 2019, floods covered 200.01 km^2 of watershed area (5.51% of the total watershed); in 2017, floods covered 179.59 km^2 (4.95% of the total watershed) and the year with the least flooding was 2016 with only 1.24 km^2 (representing 0.03% of the total watershed). **Table 2** shows the proportion of flooded areas**.**

Table 2.

Lam Se Bok watershed flooded area from 2005-2019.

Year		**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Area	**km^2**	5.49	27.27	36.8	8.67	17.36	83.91	113.02	7.87
	%	0.15	0.75	1.01	0.24	0.48	2.31	3.11	0.22
Year		**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	
Area	**km^2**	106.35	109.41	18.12	1.24	179.59	35.86	200.01	
	%	2.93	3.01	0.50	0.03	4.95	0.99	5.51	

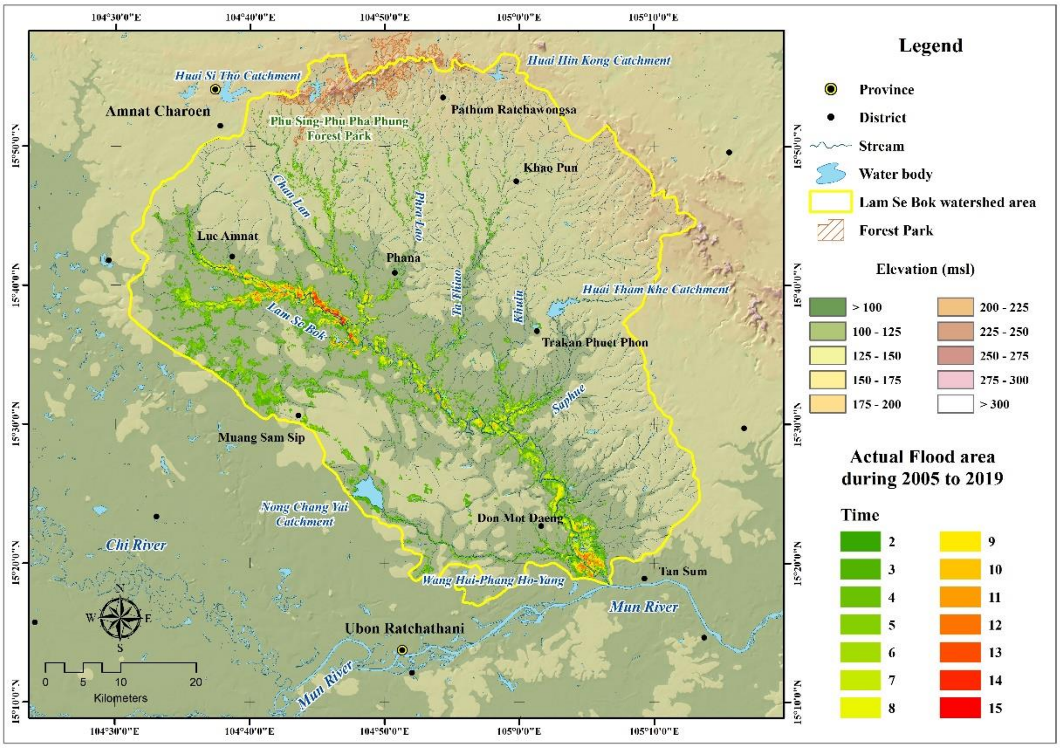

Fig. 4. Recurring flooding areas over a period of 15 years (2005-2019) in LSBW area from GIS analysis.

Flood Prone area analysis by GIS resulted in a very important study: the repeating flood prone areas that appear frequently in LSBW. The results of the study showed that the repeated flooding areas that flood every year have occurred up to 15 times since 2005 in the lower area of LSBW in Na Udom village, Khok Sawang and Fa Huan village, Rai Khi sub-district, located on the south side of Lue Amnat District, Amnat Charoen Province, and in some areas of Dum Yai sub-district, Muang Sam. Sip. district, Ubon Ratchathani (**Fig. 4** and **Fig. 5**).

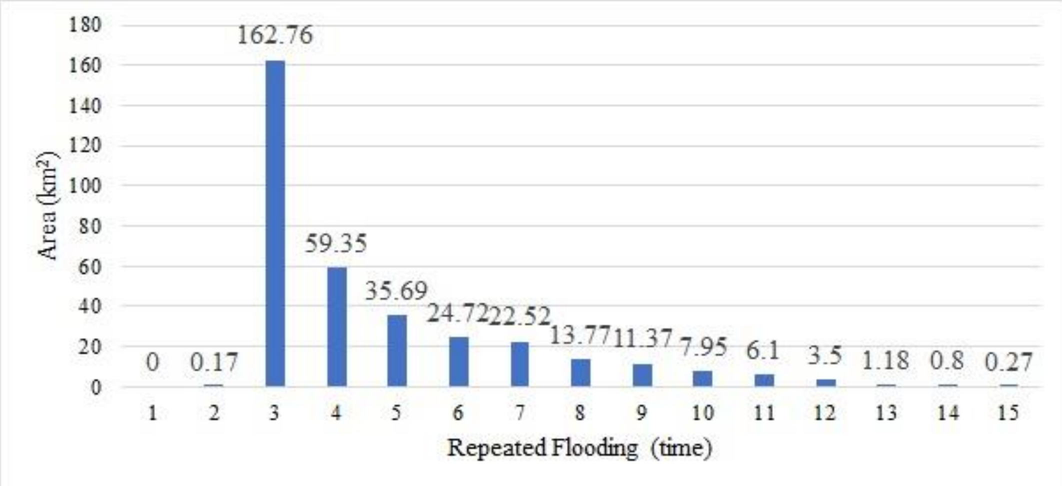

Fig. 5. Frequency data of recurring floods over a period of 15 years (2005-2019) in LSBW area.

4.2 Variables that Cause Flood Prone Areas in the LSBW

Variables that cause flood prone areas in the LSBW were obtained from Logistic Regression analysis, as shown in **Table 3**. The study results are shown using statistical value β, which variables are positive means that the higher the variable, the more susceptible to flooding. However, if the $\boldsymbol{\beta}$ value of the variable is negative means that the lower the variable, the more susceptible to flooding. (Lim & Lee, 2018).

Table 3.

Logistic regression analysis of flood prone areas and affecting factors.

Variable	β value	Exp β	Standard Error	Sig.
Elevation	-1.578	0.206	0.015	0.00
Terrain	-0.695	0.499	0.018	0.00
Slope	-0.487	0.614	0.014	0.00
Mean annual precipitation	0.100	1.106	0.004	0.00
Soil drainage	-0.469	0.626	0.009	0.00
Distance to stream	-0.079	0.924	0.009	0.00
Distance to village	-0.015	0.985	0.005	0.00
Distance to road	0.089	1.093	0.005	0.00
Land use	-0.026	0.975	0.005	0.00
Constant	4.840			
The relative operating characteristic (ROC)	0.850			

The relative operating characteristic (ROC) shows how the regression equation can be used to predict flood prone risk areas based on probability (Nandi et al., 2016; Lim & Lee, 2018; Waiyasusri & Wetchayont, 2020). The ROC values obtained for the probability of flood prone risk area was 0.85 (**Fig. 6**), which indicates a high value, since approaching 1.00 is an indication that all 9 variables are effective in analyzing flood prone areas.

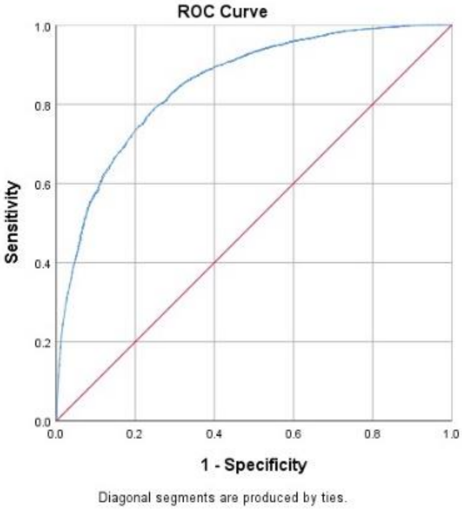

Fig. 6. The relative operating characteristic (ROC) value.

The study found that the Mean annual precipitation and Distance to road factors were the 2 variables showing positive β values. Mean annual precipitation, showing the highest value, was the most influencing factor for flooding. The average annual rainfall value with the highest average rainfall appears in the southernmost area of LSBW, which greatly affects the flooding in that area. Distance to road is also a variable that shows a positive β value. The areas that are farther from a road are indeed areas more susceptible to flooding, since the road area is engineered to elevate the road's height from its base area. The LSBW areas adjacent to roads are therefore less affected by flooding than those further away from a road.

Results showing negative β values were varied, from the highest negative to the lowest negative comprising Elevation, Terrain, Slope, Soil drainage, Distance to stream, Land use, and Distance to village, respectively. It can be seen that the top variables affecting the flood prone area in the LSBW are physical factors, especially the Elevation, Terrain, Slope, and Soil drainage variables. The lower the variable, the more susceptible to flooding, such as Elevation, Terrain and Slope, where low-lying terrain with a floodplain landform and 0-5 degrees of slope is easy to become a flood prone area. For Soil drainage, the low value represents soil types that are very poor and with a poor priority drainage system, causing the water mass to be immersed in the area. As the area is covered with hygroscopic clay and clay loam, the above physical factors are hallmarks of this LSBW area.

With the Distance to stream, Land use, and Distance to village variables, the study found that the lower the three variables, the more susceptible to flooding. The results showed that when the Distance to stream variable was closer to a water source, the more susceptible it was to flooding. Distance to stream and Distance to village variables affecting the susceptibility to flood prone areas in LSBW, both are at a level not exceeding 500 m. Regarding the Land use variable, the low value represents land use conditions for cultivating and farming, as the LSBW is mainly engaged in paddy cultivation planted on low slopes and floodplain. With the Distance to village variable, the results showed that the closer to the village area, the easier it was to create a flood prone area. Since these areas do not have an efficient drainage system, it often floods in the villages.

The results of all the variables that are indicators of flood prone areas were analyzed for a Flood Prone Risk area map in LSBW. With this we can create a spatial database for effective management of flood prone areas.

4.3 Flood Prone Risk Area Map in LSBW

The study results of flood prone risk areas in LSBW by logistic regression statistical analysis, β value as a database and spatial analysis using GIS, were used to create maps for watershed disaster management (**Fig. 7**), as Eq. (2).

$$Y = 4.840 + (-1.578 * \text{"Elevation"}) + (-0.487 * \text{"Slope"}) + (-0.695 * \text{"Terrain"}) + (-0.469 * \text{"Soil\_drainage"}) + (-0.026 * \text{"Landuse"}) + (0.100 * \text{" Mean\_annual\_precipitation"}) + (-0.079 * \text{" Distance\_to\_stream"}) + (0.089 * \text{" Distanc\_ to\_road"}) + (-0.015 * \text{" Distance\_to\_village"}) \quad (2)$$

Flood Prone Risk area map in LSBW has classified risk levels according to criteria, which can be described into the following categories: Very low (0 - 0.20), Low (0.21 - 0.40), Medium (0.41 - 0.60), High (0.61 -. 0.80) and Very high (0.81 - 1.00) (Ma et al., 2019). The β value results of the variables led to the highlight of this research; also, the risk level could be expressed as spatial data, as follows. The very high level flood prone risk areas, with a total area of 638.59 km^2 (17.59%), are mostly low-elevation areas and areas with high annual average rainfall, which appear around the middle and end of the LSBW near Lue Amnat and Phana District, Amnat Charoen Province; and Trakan Phuet Phon, Tan Sum, Don Mot Daeng, and Muang Sam Sip, Ubon Ratchathani Province. The high-risk area covers a wide area in the middle of the LSBW, as it is a floodplain terrain and has an elevation of only 100-200 m, so it is susceptible to flooding.

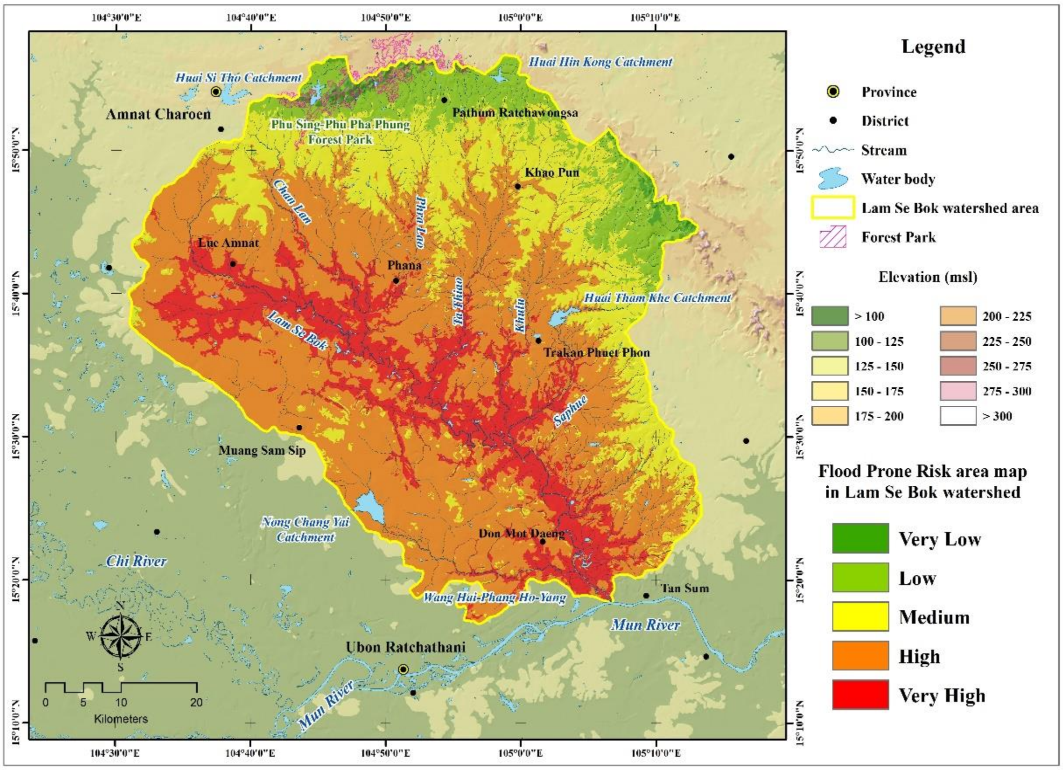

Fig. 7. Flood Prone Risk area map in LSBW.

High level flood prone risk areas cover an area of 1,848.10 km^2 (50.92%). Medium flood prone risk areas cover 794.95 km^2 (21.90%). Low flood prone risk areas cover 310.86 km^2 (8.56%), the least vulnerable to flooding encompassed 46.35 km^2 (1.27%). The least vulnerable to flooding in LSBW is located in Phu Sing-Phu Pha Phung Forest Park, the northern and northeastern slopes of LSBW.

This study developed the feasibility and credibility by applying results from the logistic regression model and validating the actual flood area. Actual flood area data is a collection of information from flood related agencies at local, central level and community policy participation in order to know how to manage the flood by creating flood-vulnerable maps (Dastgerdi et al., 2019; Seebauer & Babcicky, 2017). The validation results between the actual flood area data and the Flood Prone Risk area map from the logistic regression model were as shown in **Table 4**, where the results showed that during the 15 years of repeated flooding. Flood cover area of up to 228.26 km^2, representing 65.19 %. Relation level of the two datasets had a good level of reliability.

Table 4.
The validation results between the actual flood area data and the Flood Prone Risk area map.

Repeated flooding	Flood Prone Risk area (km^2)					Actual Flood area (km^2)
	Very Low	Low	Medium	High	Very High	
1	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.17	0.00	0.17
3	0.00	0.50	7.53	71.66	83.12	162.81
4	0.00	0.03	1.10	21.81	36.39	59.33
5	0.00	0.00	0.21	11.15	24.26	35.62
6	0.00	0.00	0.03	3.75	20.93	24.71
7	0.00	0.00	0.00	1.29	21.18	22.47
8	0.00	0.00	0.00	0.88	12.97	13.85
9	0.00	0.00	0.00	0.79	10.58	11.37
10	0.00	0.00	0.00	0.37	7.57	7.94
11	0.00	0.00	0.00	0.27	5.82	6.09
12	0.00	0.00	0.00	0.29	3.23	3.52
13	0.00	0.00	0.00	0.02	1.16	1.18
14	0.00	0.00	0.00	0.01	0.79	0.80
15	0.00	0.00	0.00	0.00	0.27	0.27
Sum	0.00	0.53	8.87	112.46	228.27	350.13
%	0.00	0.15	2.53	32.12	65.20	

5. CONCLUSIONS

Floods are disasters that occur almost every year during the monsoon season in Thailand, especially in the watershed areas of Northeast Thailand which are often affected by such disasters. This research aims to solve this problem by analyzing individual factors to find solutions to the causes of floods by using logistic regression analysis in conjunction with GIS to create a Flood Prone Risk area map in LSBW.

One of the objectives of this paper is to find the most influential variables of flood prone occurrence. Based on our results of logistic regression analysis, the order of flood conditioning factors for negative β values were the Elevation, Terrain, Slope, Soil drainage, Distance to stream, Land-use, and Distance to village variables, respectively. The positive β values were Mean annual precipitation and Distance to road, respectively. It was found that the very high-level flood prone risk areas, with a total area of 638.59 km2 (17.59%), high level flood prone risk areas cover an area of 1,848.10 km2 (50.92%). Medium flood prone risk areas cover 794.95 km2 (21.90%). Low flood prone risk areas cover 310.86 km2 (8.56%), the least vulnerable to flooding encompassed 46.35 km2 (1.27%). The important variables are low-elevation areas and areas with high annual average rainfall which are mostly located at the middle and southern end of the LSBW.

This research shows that the utilization of a flood prone risk map is a useful basis for taking preventive actions to mitigate floods and expedite relevant agencies to assist those areas at highest risk for flood mitigation and land use planning. Although this risk map is suitable for watershed terrain, the context of flooding and other relevant factors affecting flooding should be investigated for effective logistic regression analysis if used in other areas.

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