# Enhancing Flood Susceptibility Mapping Through Machine Learning and Multi-Criteria Decision-Making Techniques

Sangey Pasang[1], Tashi Tenzin Dorji[2*], Tshewang Zangmo[3], Pema Thinley[4]

[1, 2, 3]Civil Engineering Department, College of Science and Technology, Royal University of Bhutan
[4]Information Technology Department, College of Science and Technology, Royal University of Technology
E-mail: sangeypasang.cst@rub.edu.bt[1], tashitenzindorji55@gmail.com[2*], zangmotshewang101@gmail.com[3], pemathinley.cst@rub.edu.bt[4]

*Received: 14 April 2025; Revised: 9 June 2025; Accepted: 12 July 2025; Published: 17 August 2025*

**Abstract**

Flooding has historically caused massive social, economic and environmental damage affecting lives and livelihood. There is a concerted effort to study the phenomenon of flooding, hazard assessment, mitigation and prevention of flood and associated risks. In the planning phase, Flood Susceptibility Mapping (FSM) to identify vulnerable areas are useful to provide critical data for preparedness, risk management, and sustainable land use planning. Most flood susceptibility maps are generated using multi-criteria Decision models (MCDM) and Machine Learning models. The reliability and accuracy of Flood Susceptibility Maps are increased by systematic evaluation of multiple flood related factors and their interrelationship which are more easily analyzed by machine learning models. Therefore, the aim of the study is to develop FSM for Toorsa River and the Pasakha River. using the two multi-criteria Decision models, the Shannon Entropy model and the Criteria Importance Through Intercriteria Correlation method. Further FSM were also developed using two machine learning algorithms of Random Forest and Support Vector Machine. Factors such as elevation, slope, soil type, and land use/land cover, rainfall, and Topographic Wetness Index were assigned weights based on the two MCDM techniques to develop the maps. Similarly, the same factors were used for training ML models and validating their performance in flood-prone area classification. The results of the study shows that Area Under Curve scores were high (0.98) in both the study area using Random Forest while the lowest score of 0.21 was obtained for Pasakha river using the Shannon Entropy Model. In general the Machine Learning models are found to be more accurate, which may be attributed to its ability to interpret data in a non-linear manner unlike the MCDM methods. The final Flood Susceptibility Maps of the study area were produced based on Random Forest models, as it provided the most accurate results.

***Key Words:*** *Flood susceptibility mapping, multi-criteria Decision models, Machine Learning, Criteria Importance Through Intercriteria Correlation, Shannon Entropy Model, Random Forest, Support Vector Machine*

## 1. INTRODUCTION

As a natural aspect of the hydrological cycle, flooding poses significant risks, including potential fatalities, population displacement, and environmental damages (Hagos et al., 2022). Some of the major contributing factors that cause flooding are heavy rainfall, ice jams, snowmelt, and changes in land use such as deforestation and urbanization (Rincón et al., 2018). Due to climate change, there is an increase in the frequency of river floods and flash floods that occur due to severe rains, snow melting, or dam collapse (Ardalan et al., 2009; Hosseini et al., 2020; Sharifi et al., 2012; Andaryani et al., 2021). This may be aggravated by the growing population along the river basins which could lead to a gradual decline in the land cover and increase in the sediment supply to the water bodies (Ahmed et al., 2024).

Floods have become one of the most severe catastrophes compared to any other form of natural disaster. It affects the greatest number of individuals around the world (Ghosh et al., 2023) with the developing nations facing an increased risks (Singha et al., 2024) and suffering a much greater impact on their Gross Domestic Product (Ardalan et al., 2009). In 2021, in a single year, there were 206 major floods recorded in the world that affected 29.2 million people and 4393 deaths (Maharjan et al., 2024). In Bhutan, several flooding events due to the glacial lake outburst floods and surface runoff during monsoon are common occurrences. The frequency of major flood events in Bhutan has been increasing, with over 60 major floods occurring between 1968 and 2016 (NCHM, 2018). The flood events that occurred within the Punatsangchhu river basin in

1968, 1987, and 1994 were due to the GLOFs event and the highest flood events occurred during the monsoon seasons causing infrastructure damage and economic loss (Tempa, 2022). Additionally, a recent flash flood event at Toorsa, Phuentsholing caused severe damage to the infrastructure nearby and the property (BBS, 2023). Therefore, there is an urgent need to establish an effective mitigative flood management strategies in this mountainous nation. One of the tools commonly used to support decision-making in risk management, to assist in implementing effective mitigative strategies for the floods and guide sustainable land use planning in high-risk areas is Flood Susceptibility Mapping (FSM) (Vojtek & Vojteková, 2019).

FSM is the vital process of identifying areas that are prone to flooding by providing critical data for disaster preparedness and mitigation efforts (Vojtek & Vojteková, 2019). FSM involves analyzing the physical characteristics of the topography, such as land use and land cover, slope, elevation, and soil type to identify flood-prone regions (Lee & Kim, 2021). With the change in the climate and the rising of sea levels, an accurate FSM is crucial to mitigate the environmental, socio-economic impacts of the flood. Some of the methods employed in FSM are Multiple Criteria Decision Models (MCDM) such as Shannon Entropy model and Criteria Importance Through Intercriteria Correlation (CRITIC).

The Shannon Entropy model proposed in 1948 is a bivariate statistical method used to quantify disorder in thermodynamic systems which is used to assess flood vulnerability (Sharma et al., 2024). This approach evaluates the distribution of various explanatory variables and its level of contribution in creating the most favorable conditions for flood inundation occurrences. The higher value of entropy value will show that there is more randomness and vice versa (Arora et al., 2021).

CRITIC is a technique that is used to calculate the objective weights' relative importance in MCDM methods (Diakoulaki et al., 1995). This technique, termed by Diakoulaki, Mavrotas, and Papayannakis in 1995 is an efficient tool for determining the weights of the attributes. This method considers the standard deviation of each criterion to capture the variability of the data and considers the correlation between criteria to understand their redundancy which is different compared to Shannon Entropy where only the variability is considered (Krishnan et al., 2021). One of the advantages of using this method is that while assigning the weights, CRITIC will need to only analyze the data and draw all its conclusions to assign the weights from the data provided to it. So, the efficiency of this method will rely primarily on the quality of the data provided.

Additionally, the use of Machine Learning (ML algorithms is increasing over the years for the flood risk assessment due to its effectiveness of learning the relationships (Demissie et al., 2024). The random forest (RF) and support vector machine (SVM) are the two ML algorithms that will be used for development of FSM for Toorsa and Pasakha. Area Under Receiver Operating Characteristic Curve will be used for assessing the model accuracy.

The aim of the current study is to assess the usefulness of Multi-Criteria Decision-Making (MCDM) and Machine Learning (ML) techniques for the development of FSM. A detailed susceptibility map will be produced by utilizing the most accurate outputs. This may be used to enhance flood management strategies and improve disaster preparedness.

## 2. STUDY AREA

Phuentsholing, situated in the southern part of the country, is highly susceptible to flooding due to its geographical location and the presence of numerous tributaries contributing to the hydrology of the region. These tributaries, combined with the intense monsoon rainfall, make the area more vulnerable to flash floods. The maximum rainfall of 495.3 mm recorded in the Phuentsholing area, as per National Centre for Hydrology and Meteorology (NCHM), occurred on August 2, 2000. In the current study, two key areas of Amo Chu Basin and Pasakha Basin were considered.

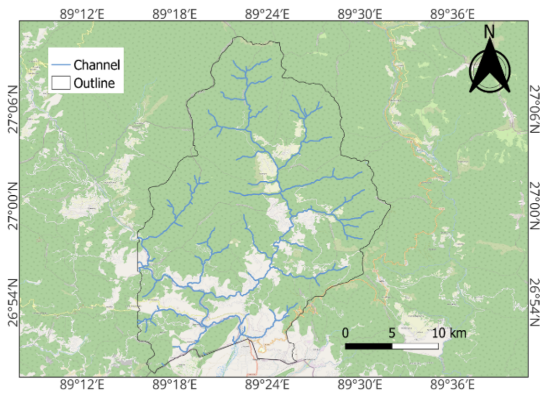



***Fig. 1:*** *Study Area of Amochu River basin*

Amochu basin (Fig.1) encompasses an area of 649.98 $km^2$ with Amochu (Toorsa River) as the principal river. It is subject to flooding events mostly during the monsoon season. The recent flash flood on 13 July 2023 affected 6 NHDCL housing units and 3 other private buildings causing major property losses and damage to infrastructure.

The second basin (Fig. 2) is considered in Pasakha encompassing an area of 72.01 $km^2$. Two major rivers in the basin are Barsa River and Singye chu. The Barsa River has been subjected to a number of floods with resulting damages to several residential areas, power lines, and industries in the past (Dorji, 2022). Singye River is less frequently subjected to flood even during the rainy season.

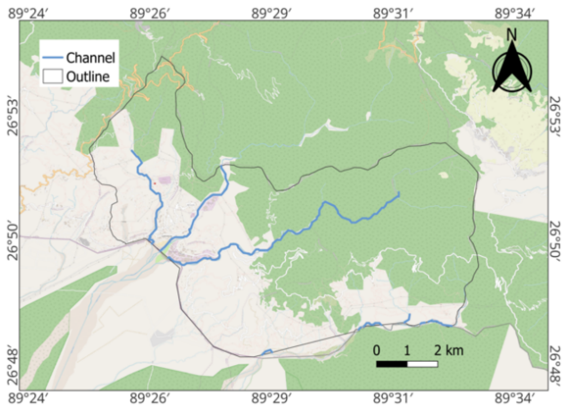



***Fig.2:*** *Study Area of Pasakha River basin*

## 3. METHODOLOGY

The methodology flow chart in Fig. 3 provides a brief overview of the procedure of the study. The data on slope, soil type, elevation, LULC, TWI and Rainfall are applied in the study. Models are developed using both MCDM and ML methods. Validation is done using Area Under Curve method.

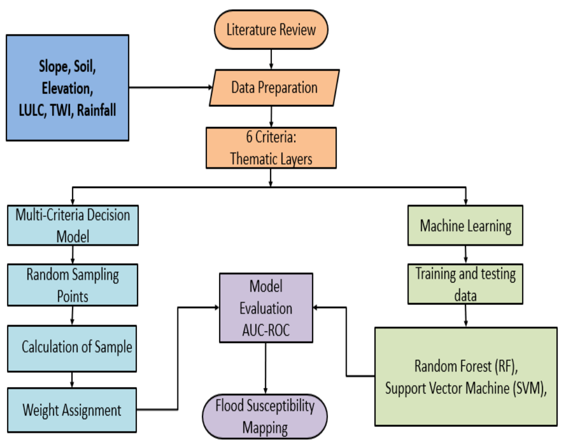



***Fig.3:*** *Methodology chart*

### 3.1 Factors Influencing Flooding

The following factors that contribute to the flood for the study area for the accurate flood susceptibility mapping were considered:

- Slope

Steeper slopes result in faster runoff, which can increase the likelihood of flooding and contribute to flash floods. Conversely, flatter areas with low slopes may experience water stagnation, eventually leading to flooding overtime. The maximum slope is 71.23 in Toorsa whereas a maximum value of 66.88 as given in Fig. 4.

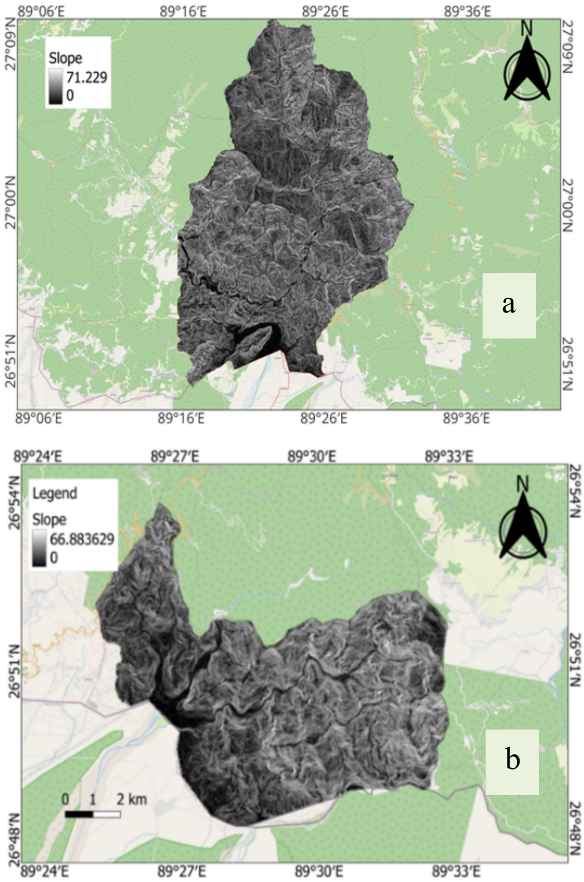



***Fig. 4:*** *Slope map (a) Amochu and (b) Pasakha*

- Rainfall

Rainfall is a crucial factor that influence floods at a particular place. The daily rainfall data was extracted from the center for hydrometeorology and remote sensing (CHRS) website that has easy access to satellite-based precipitation for the year 2024. The thematic layers for the rainfall extracted for the year 2024 are shown in Fig. 5 below.

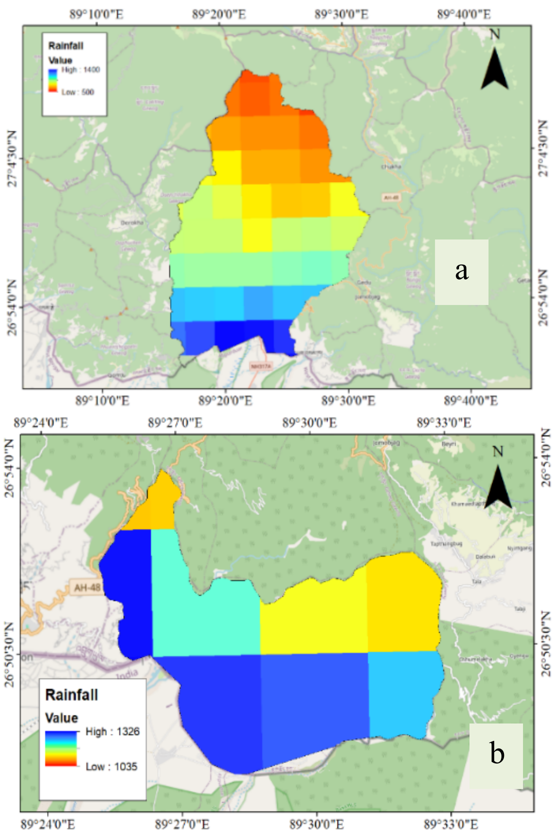
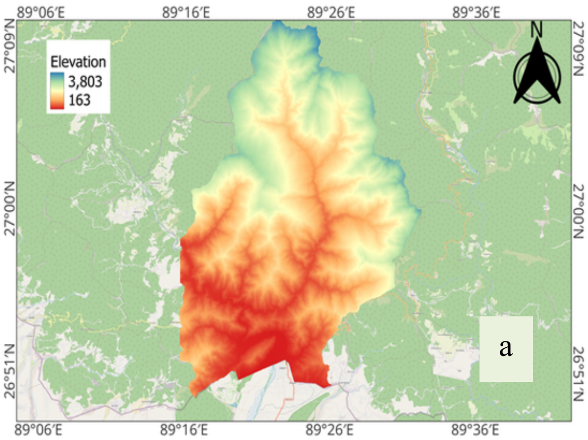



*Fig. 5: Rainfall map (a) Amochu and (b) Pasakha*

- Elevation

Areas at higher elevations are generally less susceptible to flooding, while lower-elevation regions are more susceptible. Low-lying areas often face recurrent flooding, especially during heavy rainfall, highlighting elevation as a key factor influencing flood risk. (Veerappan & Sumaira, 2020). The elevation maps of the study area given in Fig. 6 depict an elevation variation from 163 m to 3803 m in the basins.



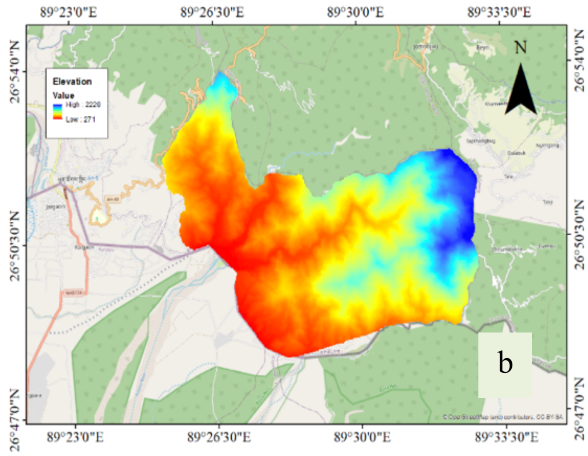




*Fig. 6: Elevation map (a) Amochu and (b) Pasakha*

- Land use and Land cover

Build areas with impermeable surfaces, such as roads and buildings, experience higher runoff, making them more susceptible to flooding. In contrast, areas with forests or natural vegetation absorb more rainfall, lowering flood susceptibility (Shafapour et al., 2017). The upper reaches of both the basins are largely forested areas. Percent built up area is higher in Pasakha as shown in Fig. 7.

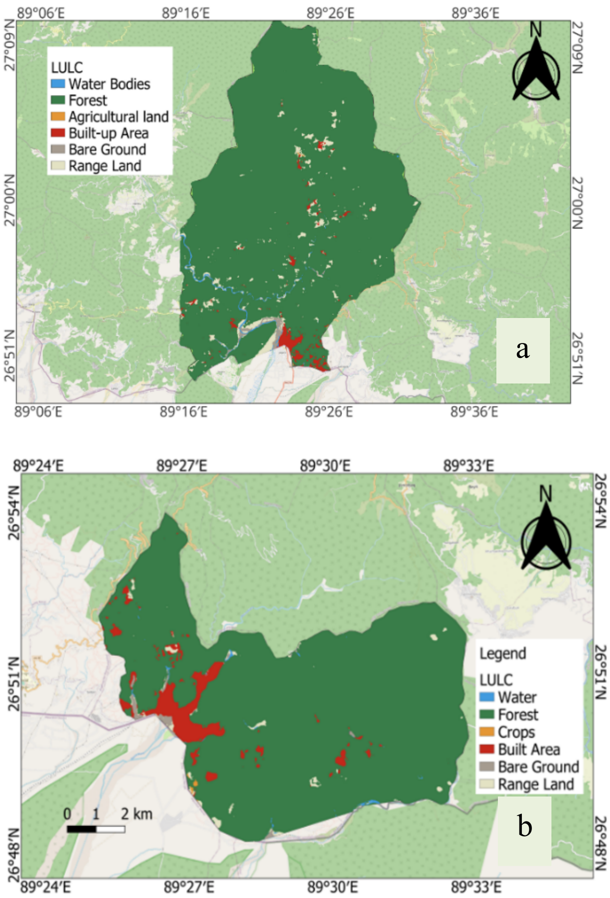



*Fig. 7: LULC map (a) Amochu and (b) Pasakha*

- Soil Type

The permeability of the soil plays a very important role in flood susceptibility. Highly permeable soils allow water to infiltrate more easily, decreasing the risk of flooding, whereas less permeable soils can cause surface runoff and increase flood risks (Mojaddadi et al. 2017). Dystric Cambisols dominates in both the basins with skeletic Cambisols.

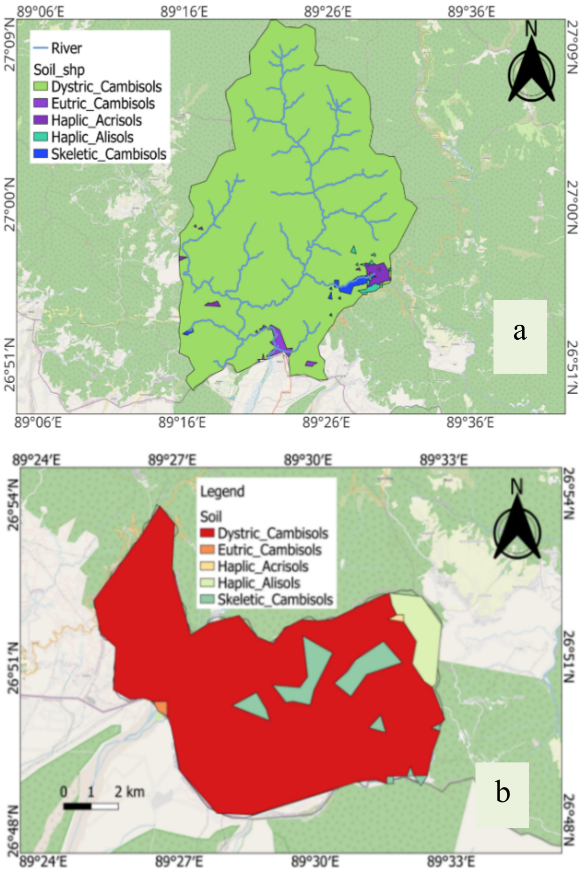
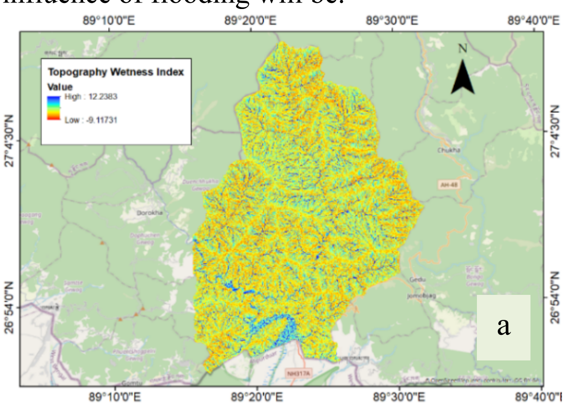



***Fig. 8:*** *Soil map of (a) Amochu and (b)Pasakha*

- Topographic Wetness Index (TWI)

It is the numerical indicator that represents the spatial distribution of elements like soil moisture, water table depth and the soil wetness. The higher the value of the TWI, the higher the influence of flooding will be.



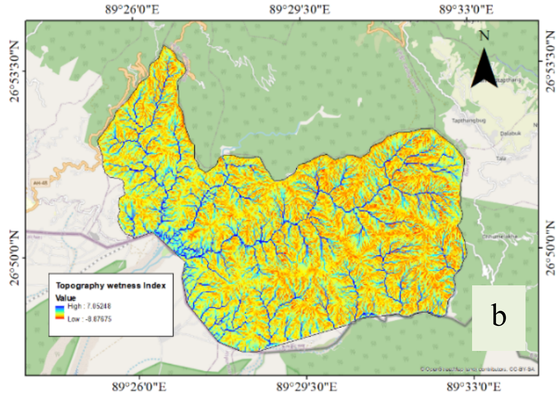




***Fig .9:*** *TWI map (a) Amochu and (b)Pasakha*

The highest TWI values are 12.23 and 7.05 for Amochu and Pasakha area respectively as shown in Fig.. 9.

### 3.2 Shannon Entropy Model

In Shannon Entropy Model, the total number of points and the number of points within the mentioned range of each factor were determined and tabulated. For each range or the class of factors the probability density or the normalized probability is determined by using the formula:

$$P_i = \frac{No. of\ points\ in\ each\ class\ range}{Total\ number\ of\ points}$$

Then, the Entropy value for each factor is evaluated and maximum entropy is also calculated.

$$H_j = \sum_{i}^{sj} P_{ij} \times Log_2 P_{ij}$$

$$H_{jmax} = log_2 S_j$$

Where, Pi = Probability density

$H_i$ & $H_{jmax}$ = Entropy Value

$S_j$ = Number of Classes or range

The Information Coefficient ($I_j$) and the resultant weight value ($W_j$) is then calculated by using the formula:

$$I_j = \frac{H_{jmax} - H_j}{H_{jmax}}$$

$$W_j = I_j \times P_i$$

### 3.3 Criteria Importance through Intercriteria Correlation (CRITIC)

In this model, the data used in Shannon Entropy model is also used. Relevant numerical values were assigned to the Soil and Land Use Land Cover. The min-max normalization method was used to standardize the data as all the parameters need to be on a comparable scale using the equation:

$$Z = \frac{X - mean(X)}{std(X)}$$

After computing the standard deviation for each criterion and the correlation matrix, the CRITIC weights was calculated using the equation below.

$$wj = \frac{\sigma j(1 - \Sigma Correlations\ of\ j)}{\Sigma\sigma(1 - \Sigma Correlations)}$$

Where, wj= weight of criterion

$\sigma j$=standard deviation of criterion

### 3.4 Machine Learning Algorithms

Two ML algorithms, the Random Forest (RF) and Support Vector Machine (SVM) were used for generating the FSM for the two study sites. The RF algorithms are supervised learning and most used for the FSM (Seleem et al., 2022). The method divides the input dataset through bootstrap sampling into multiple subsets while producing a decision tree for each section. The prediction process depends on a collective decision derived from all trees through voting to produce more reliable results and minimize fitting errors.

SVM is a supervised machine learning which creates a hyperplane that separates the flood and non-flooded points in the flood susceptibility mapping (Seleem et al., 2022). SVM functions create the largest possible separation between classes through the analysis of vital data points which it identifies as support vectors. SVM employs kernel functions to create a non-linear transformation that separates unclassifiable data into distinct dimensions for boundary definition. Of the four types of kernel functions linear, radial basis function, sigmoid kernel and polynomial kernel, radial basis function was incorporated in the present study as it has high accuracy.

## 4. RESULTS AND DISCUSSION

### 4.1 Shannon Entropy Method

For FSM based on the Shannon entropy approach, the six factors were assigned weights based on their contribution to the occurrence of flood. The results of the Shannon Entropy Model analysis show that the most significant factors are Soil type and LULC in both the catchments as shown in Table 1.

Using the weights obtained, the weighted overlay method was used to generate the flood susceptibility map. Flood susceptibility maps (Fig. 12) were then generated using the weights obtained from Shannon Entropy using the Weighted-overlay tool from ArcMap.

***Table 1**: Shannon Entropy weights*

| SN | Factors | Weights | |
|---|---|---|---|
| | | **Amochu** | **Pasakha** |
| 1 | Slope | 0.09 | 0.05 |
| 2 | Elevation | 0.05 | 0.06 |
| 3 | Rainfall | 0.03 | 0.14 |
| 4 | TWI | 0.08 | 0.07 |
| 5 | Soil | 0.37 | 0.39 |
| 6 | LULC | 0.38 | 0.29 |

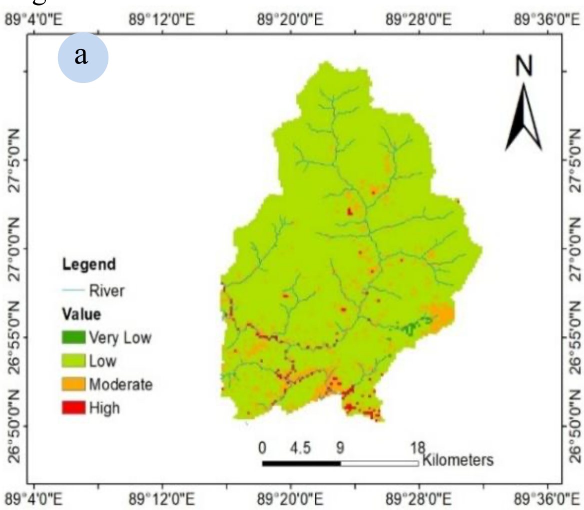
### 4.2 CRITIC method

In this method based on the weights, the critical factors for the Amochu area are elevation and rainfall, whereas TWI is the most significant factors as shown in Table 2.

***Table 2:** CRITIC weights for the two study areas*

| SN | Factors | Weights | |
|---|---|---|---|
| | | **Amochu** | **Pasakha** |
| 1 | Slope | 0.19 | 0.13 |
| 2 | Elevation | 0.26 | 0.16 |
| 3 | Rainfall | 0.26 | 0.18 |
| 4 | TWI | 0.24 | 0.2 |
| 5 | Soil | 0.03 | 0.18 |
| 6 | LULC | 0.02 | 0.15 |

The weights derived from the CRITIC method were then used to develop the FSM as shown in Fig. 12.



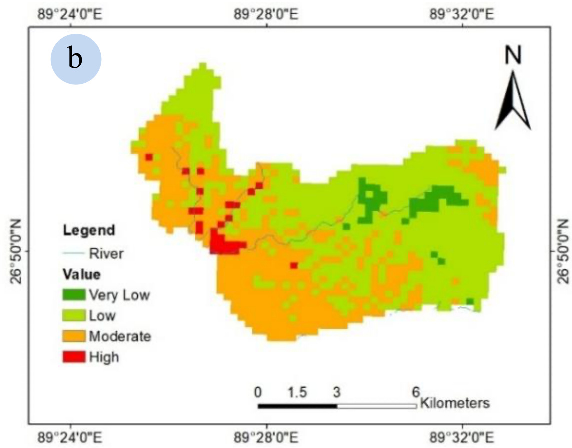



*Fig. 10: FSM from Shannon Entropy Weight for (a)Amochu and (b) Pasakha*

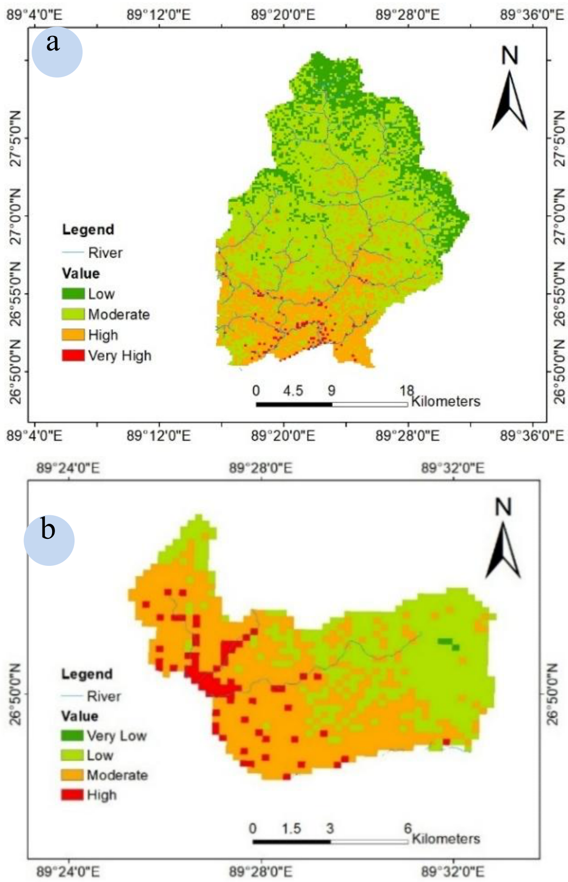



*Fig. 11: FSM from CRITIC Weight (a) Amochu and (b) Pasakha*

## 4.3 Random Forest method

Based on the RF model, feature importance was identified, and the main factors that determine the occurrence of flooding were deduced. In Pasakha, the Topographic Wetness Index was established as the leading factor, whereas, in Amochu the elevation and slope were determined as the influential factors as shown in Fig. 12.

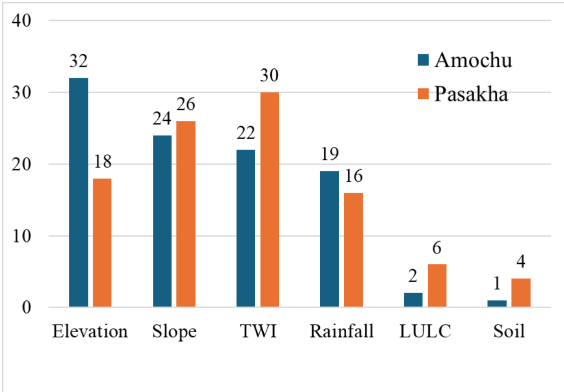



*Fig. 12: Feature importance in RF model*

## 4.4 Support Vector Machine method

Similarly, using the SVM model, the feature importance was calculated to determine the most influential factor. For Pasakha, the topographic wetness index was the dominant factor whereas for Toorsa elevation contributes the most to flooding.

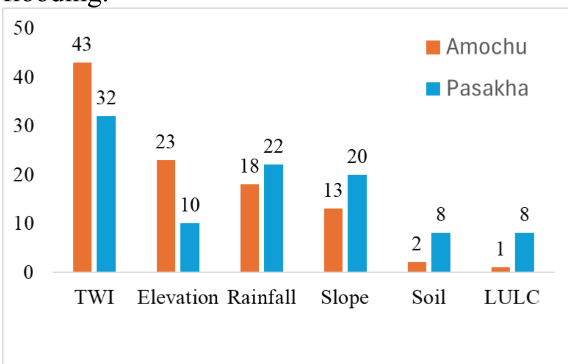
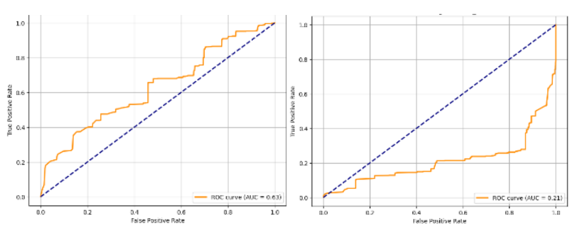



*Fig. 13: Feature importance in SVM model*

## 4.4 Model validation

To assess the model accuracy, Receiver Operating Characteristic (ROC) curve was applied and Area Under Curve (AUC) score was computed. The ROC-AUC curves obtained for various methods are shown in Fig. 14 while the AUC values are given in Table 3. When AUC is equal to 1, it implies that prediction is perfect, an AUC value of 0.5 implies that the model simply does not perform better than random guessing. If the AUC is less than 0.5, it means that random guesses would perform better.



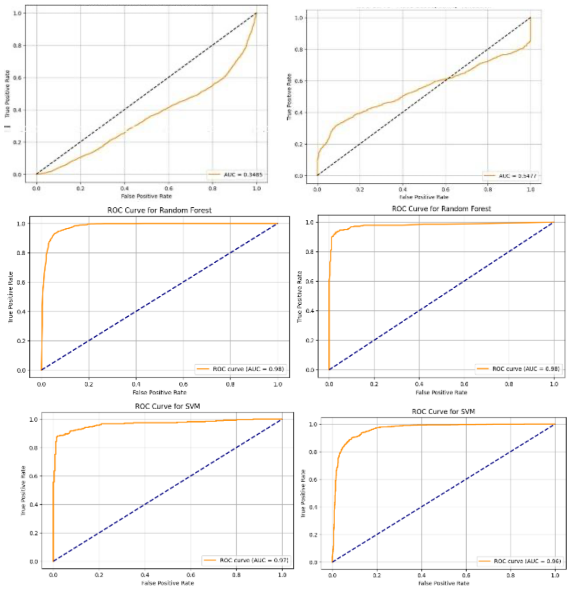
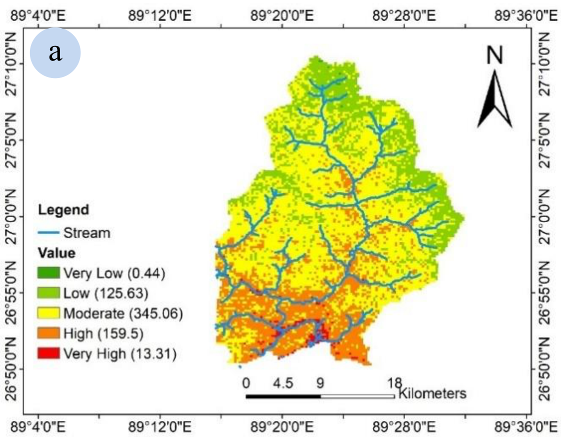



***Fig. 14:*** *ROC-AUC for Amochu(left) and Pasakha (right) using (top to bottom) 1. Shannon Entropy method, 2. CRITIC method, 3. Random Forest Method and 4. SVM method*

***Table 3:*** *ROC-AUC values for various models*

| SN | Methods | ROC-AUC values | |
|---|---|---|---|
| | | **Amochu** | **Pasakha** |
| 1 | Shannon Entropy Method | 0.61 | 0.21 |
| 2 | CRITIC method | 0.3485 | 0.5477 |
| 3 | Random Forest | 0.98 | 0.98 |
| 4 | Support vector Machine | 0.96 | 0.97 |



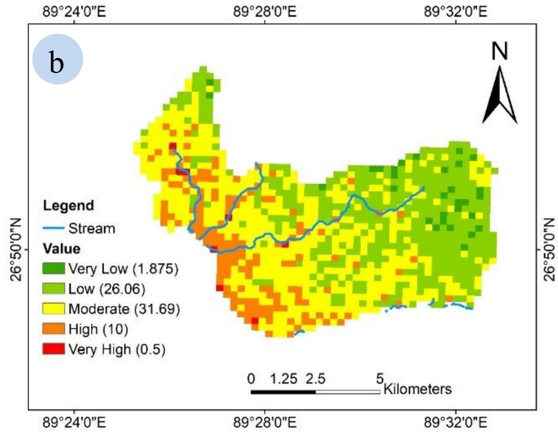




***Fig. 15:*** *Final FSM of (a) Amochu and (b)Pasakha*

From Table 3 above, the highest value of AUC was obtained for RF model with a value of 0.98. Because of its high predictive accuracy, the RF model was adopted for developing flood map decisions for each study region through its adoption for model construction. Therefore, the final flood susceptibility maps shown in Fig. 14 were developed based on the RF model.

## 5. CONCLUSION

This project aimed to develop a FSM using different MCDM and ML algorithms. Flood susceptibility maps can be a crucial tool for reducing the risk of flooding as they allow decision makers to know the more dangerous areas to apply mitigation methods. Using multiple methods and comparing the results provides a more accurate map. In this project, after comparing four different methods, two of them MCDM and the other two ML, the superiority of the ML algorithms is evident.

While the generation of the flood susceptibility map was successful for all the methods, upon validation, it is evident that the modern machine learning techniques outperform the MCDM methods. The data type used by all the study areas for each method has been kept the same for comparison. Proper extraction of data and data cleaning were executed in the same to prepare the data to be used by all the algorithms. The parameters slope, elevation, LULC, Soil, Rainfall, and Topographic Wetness Index were all given equal importance in the initial stage of the project to reduce any bias.

The Shannon Entropy model resulted in AUC scores for Toorsa and Pasakha were 0.63 and 0.21 respectively while the CRITIC method produced 0.3485 for Toorsa and 0.5477 for Pasakha. These values are very low compared to the AUC scores of the ML models in which the

RF model produced an accuracy score of 0.98 in both study areas while the SVM model produced 0.96 for Toorsa and 0.97 for Pasakha.

The reason for such a massive gap in accuracy score could be due to the methods of how each models handles and interprets the data. The two MCDM methods used only focused on the entropy within the dataset and the linear relationship between the factors while the machine learning algorithm are able to interpret the data in a non-linear manner considering multiple scenarios. A similar study conducted on Landslide Susceptibility Map by Jari et al., 2023 also yielded similar results as this project. With the Random Forest algorithm being the model with the most accuracy, it has been adopted as the final Flood Susceptibility map for both study areas**.**

## 6. ACKNOWLEDGEMENT

We would like to show our sincere gratitude to the College of Science and Technology for this opportunity and support. The Authors also like to acknowledge the Ministry of Agriculture to provide us with the data which was crucial in our project.

## 7. REFERENCES

Ahmed, I., Das (Pan), N., Debnath, J., Bhowmik, M., & Bhattacharjee, S. (2024). Flood hazard zonation using GIS-based multi-parametric Analytical Hierarchy Process. *Geosystems and Geoenvironment*, *3*(2). https://doi.org/10.1016/j.geogeo.2023.100250

Al-Sheriadeh, M. S., & Daqdouq, M. A. (2024). Robustness of machine learning algorithms to generate flood susceptibility maps for watersheds in Jordan. *Geomatics, Natural Hazards and Risk*, *15*(1). https://doi.org/10.1080/19475705.2024.2378991

Andaryani, S., Nourani, V., Haghighi, A. T., & Keesstra, S. (2021). Integration of hard and soft supervised machine learning for flood susceptibility mapping. *Journal of Environmental Management*, *291*(December 2019), 112731. https://doi.org/10.1016/j.jenvman.2021.112731

Ardalan, A., Holakouie Naieni, K., Kabir, M. J., Zanganeh, A. M., Keshtkar, A. A., Honarvar, M. R., Khodaie, H., & Osooli, M. (2009). Evaluation of golestan province's early warning system for flash floods, Iran, 2006-7. *International Journal of Biometeorology*, *53*(3), 247–254. https://doi.org/10.1007/s00484-009-0210-y

Arora, A., Pandey, M., Siddiqui, M. A., Hong, H., & Mishra, V. N. (2021). Spatial flood susceptibility prediction in Middle Ganga Plain: comparison of frequency ratio and Shannon's entropy models. *Geocarto International*, *36*(18), 2085–2116. https://doi.org/10.1080/10106049.2019.1687594

Diakoulaki, D., Mavrotas, G., & Papayannakis, L. (1995). Determining objective weights in multiple criteria problems: The critic method. *Computers and Operations Research*, *22*(7), 763–770. https://doi.org/10.1016/0305-0548(94)00059-H

Dorji, L. (2022). Evaluating the watershed characteristics influence on the flood vulnerability of Barsa River basin to Industrial area , Pasakha-Bhutan. *January 2021*.

Ghosh, A., Chatterjee, U., Pal, S. C., Towfiqul Islam, A. R. M., Alam, E., & Islam, M. K. (2023). Flood hazard mapping using GIS-based statistical model in vulnerable riparian regions of sub-tropical environment. *Geocarto International*, *38*(1). https://doi.org/10.1080/10106049.2023.2285355

Hagos, Y. G., Andualem, T. G., Yibeltal, M., & Mengie, M. A. (2022). Flood hazard assessment and mapping using GIS integrated with multi-criteria decision analysis in upper Awash River basin, Ethiopia. Applied Water Science, 12(7), 1–18. https://doi.org/10.1007/s13201-022-01674-8

Hosseini, F. S., Choubin, B., Mosavi, A., Nabipour, N., Shamshirband, S., Darabi, H., & Haghighi, A. T. (2020). Flash-flood hazard assessment using ensembles and Bayesian-based machine learning models: Application of the simulated annealing feature selection method. *Science of the Total Environment*, *711*, 135161. https://doi.org/10.1016/j.scitotenv.2019.135161

Jari, A., Khaddari, A., Hajaj, S., Bachaoui, E. M., Mohammedi, S., Jellouli, A., Mosaid, H., El Harti, A., & Barakat, A. (2023). Landslide Susceptibility Mapping Using Multi-Criteria Decision-Making (MCDM), Statistical, and Machine Learning Models in the Aube Department, France. *Earth (Switzerland)*, *4*(3), 698–713. https://doi.org/10.3390/earth4030037

Krishnan, A. R., Kasim, M. M., Hamid, R., & Ghazali, M. F. (2021). A modified critic method to estimate the objective weights of decision criteria. *Symmetry*, *13*(6), 1–21. https://doi.org/10.3390/sym13060973

Lee, J. Y., & Kim, J. S. (2021). Detecting areas vulnerable to flooding using hydrological-topographic factors and logistic regression. *Applied Sciences (Switzerland)*, *11*(12). https://doi.org/10.3390/app11125652

Maharjan, M., Timilsina, S., Ayer, S., Singh, B., Manandhar, B., & Sedhain, A. (2024). Flood susceptibility assessment using machine learning approach in the Mohana-Khutiya River of Nepal. *Natural Hazards Research*, *4*(1), 32–45. https://doi.org/10.1016/j.nhres.2024.01.00

Mehravar, S., Razavi-Termeh, S. V., Moghimi, A., Ranjgar, B., Foroughnia, F., & Amani, M. (2023). Flood susceptibility mapping using multi-temporal SAR imagery and novel integration of nature-inspired algorithms into support vector regression. *Journal of Hydrology*, *617*(PC), 129100. https://doi.org/10.1016/j.jhydrol.2023.129100

Mojaddadi, H., Pradhan, B., Nampak, H., Ahmad, N., & Halim, A. (2017). *Ensemble machine-learning-based geospatial approach for flood risk assessment using multi- sensor remote-sensing data and GIS. 5705.* https://doi.org/10.1080/19475705.2017.1294113

Osman, S. A., & Das, J. (2023). GIS-based flood risk assessment using multi-criteria decision analysis of Shebelle River Basin in southern Somalia. SN Applied Sciences, 5(5). https://doi.org/10.1007/s42452-023-05360-5

NCHM. (2018).In *Compendium of Climate and Hydrological Extremes in Bhutan since 1968 from Kuensel* (Vol. 53, Issue 9).

Rincón, D., Khan, U. T., & Armenakis, C. (2018). Flood risk mapping using GIS and multi-criteria analysis: A greater toronto area case study. Geosciences (Switzerland), 8(8). https://doi.org/10.3390/geosciences8080275

Sharifi, F., Samadi, S. Z., & Wilson, C. A. M. E. (2012). Causes and consequences of recent floods in the Golestan

catchments and Caspian Sea regions of Iran. *Natural Hazards*, *61*(2), 533–550. https://doi.org/10.1007/s11069-011-9934-1

Sharma, A., Poonia, M., Rai, A., Biniwale, R. B., Tügel, F., Holzbecher, E., & Hinkelmann, R. (2024). Flood Susceptibility Mapping Using GIS-Based Frequency Ratio and Shannon's Entropy Index Bivariate Statistical Models: A Case Study of Chandrapur District, India. *ISPRS International Journal of Geo-Information*, *13*(8). https://doi.org/10.3390/ijgi13080297

Shafapour, M., Jebur, M. N., Honghttps, H., & Chenhttps, W. (2017). *GIS-based spatial prediction of flood prone areas using standalone frequency ratio , logistic regression , weight of evidence and their ensemble techniques. 5705.* https://doi.org/10.1080/19475705.2017.1362038

Singha, C., Rana, V. K., Pham, Q. B., Nguyen, D. C., & Łupikasza, E. (2024). Integrating machine learning and geospatial data analysis for comprehensive flood hazard assessment. *Environmental Science and Pollution Research*, *31*(35), 48497–48522. https://doi.org/10.1007/s11356-024-34286-7

Tempa, K. (2022). District flood vulnerability assessment using analytic hierarchy process (AHP) with historical flood events in Bhutan. *PLoS ONE*, *17*(6 June), 1–20. https://doi.org/10.1371/journal.pone.0270467

Veerappan, R., & Sumaira, I. S. (2020). Urban flood susceptibility zonation mapping using evidential belief function , frequency ratio and fuzzy gamma operator models in GIS : a case study of Greater Mumbai , Maharashtra , India. *Geocarto International*, *0*(0), 1–26. https://doi.org/10.1080/10106049.2020.1730448

Vojtek, M., & Vojteková, J. (2019). Flood susceptibility mapping on a national scale in Slovakia using the analytical hierarchy process. *Water (Switzerland)*, *11*(2). https://doi.org/10.3390/w11020364